

# Basics of Resting State fMRI

Intrinsic Activity  
Endogenous Oscillations  
Spontaneous Fluctuations  
Task Independent Fluctuations  
Low Frequency Fluctuations  
Default Mode

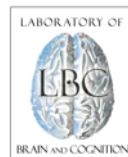
Daniel Handwerker

Section on Functional Imaging Methods

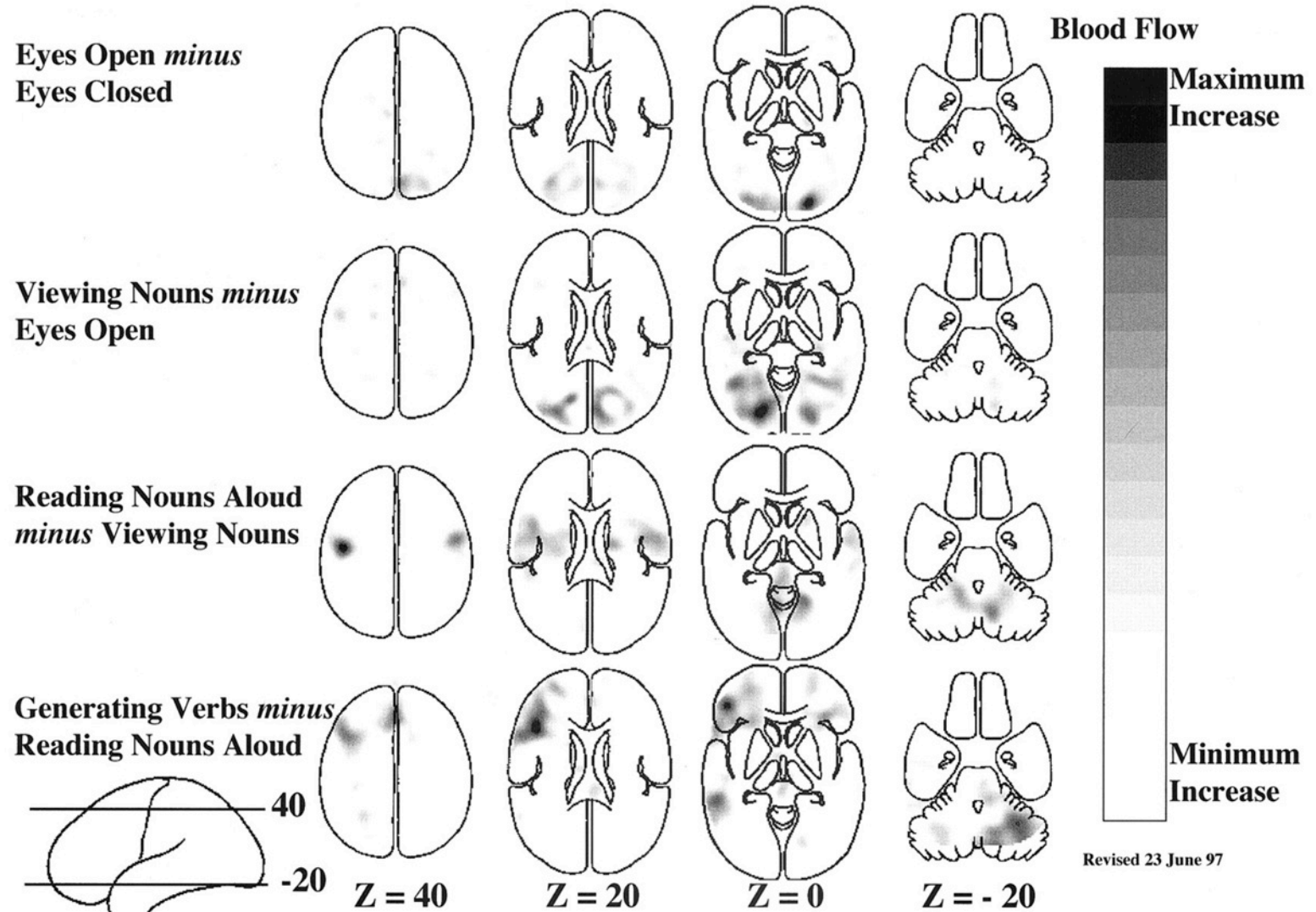
Laboratory of Brain and Cognition

National Institute of Mental Health, NIH, HHS

July 12, 2013

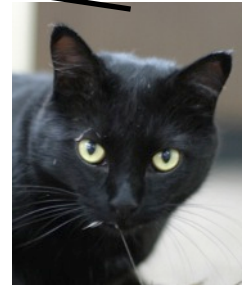
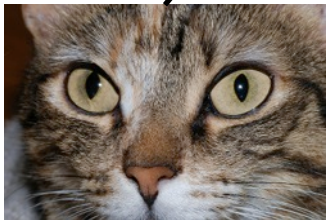
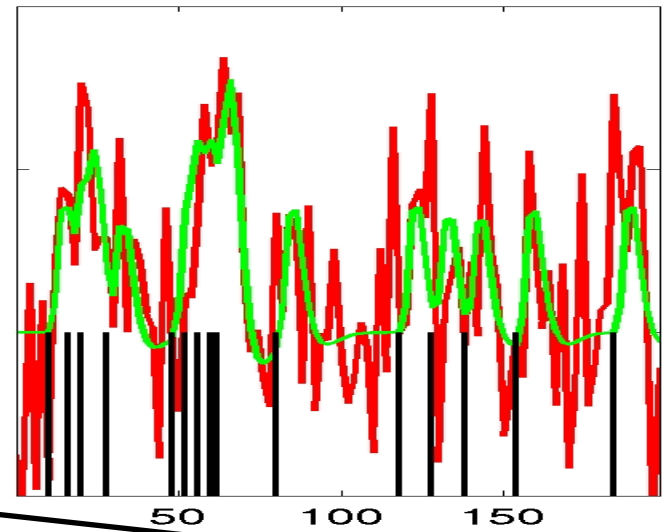
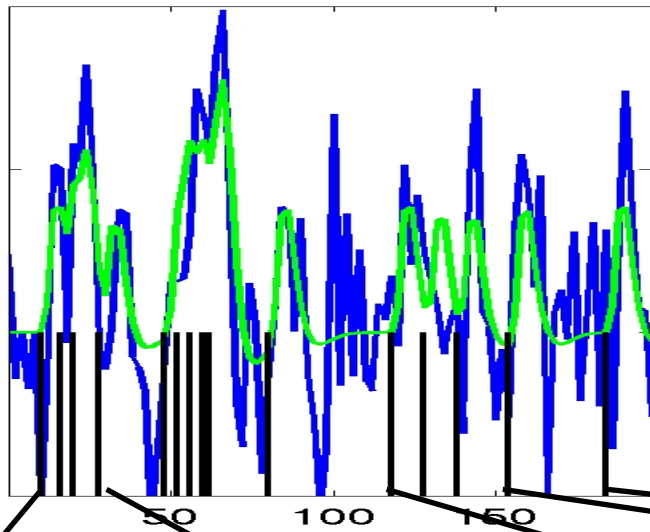


# Task-based neuroscience



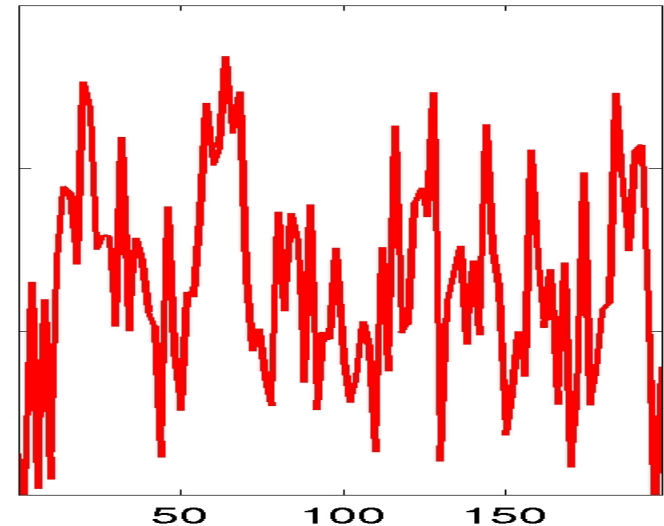
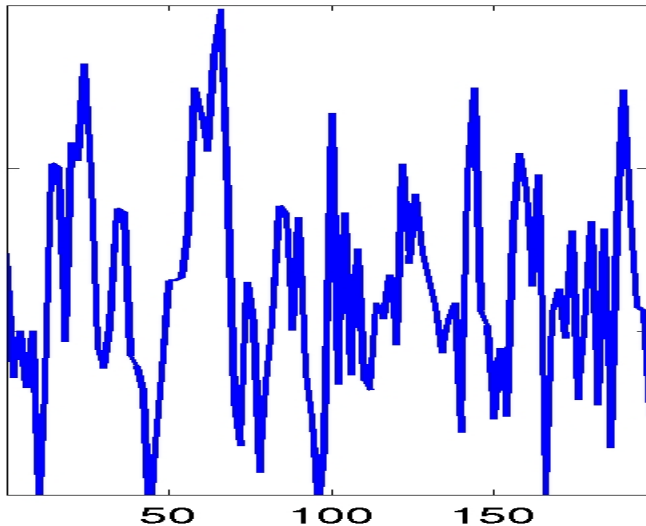
Using PET Data from the mid 1980's  
Raichle PNAS 1998;95:765-772

# Task-based fMRI

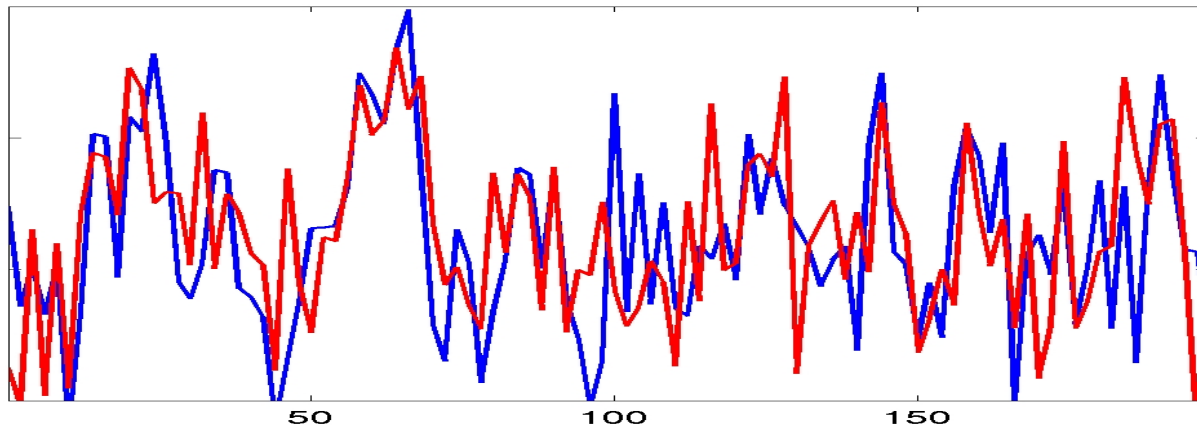


Cat images from Wikipedia

# Resting State fMRI



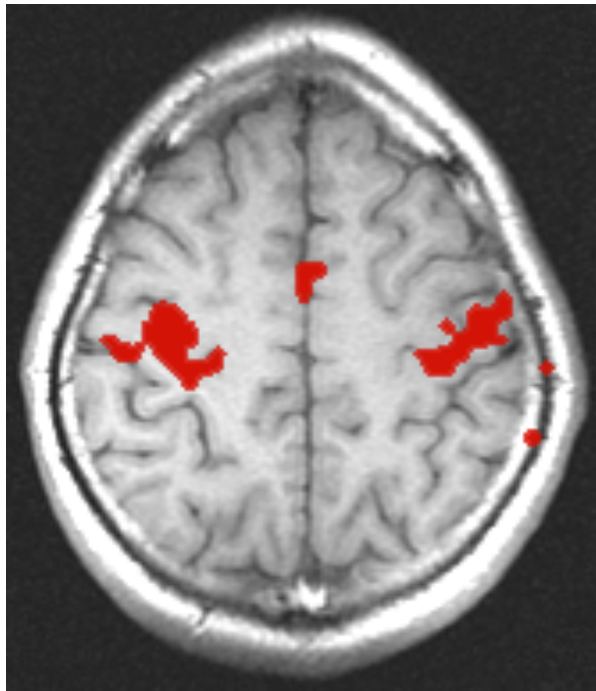
“Resting State fMRI is just task-based fMRI when you don’t know the task” –Larry Wald



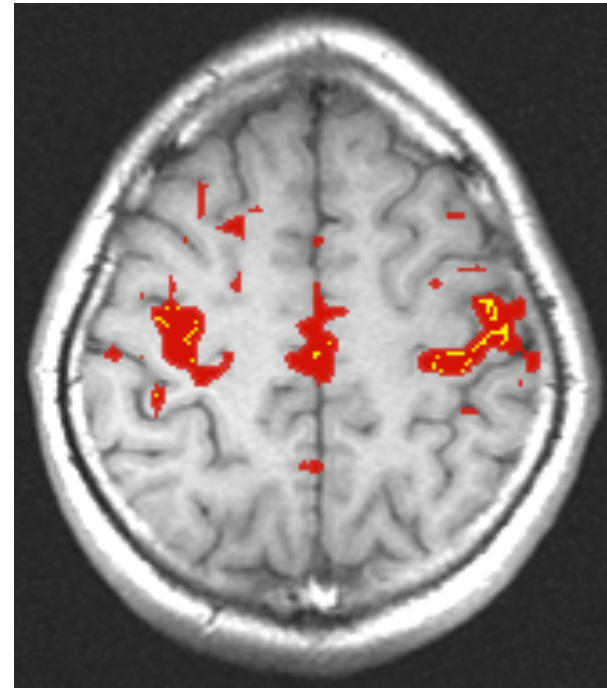
$r=0.56$



# We don't need a task to get blobs



Activation during  
finger-tapping

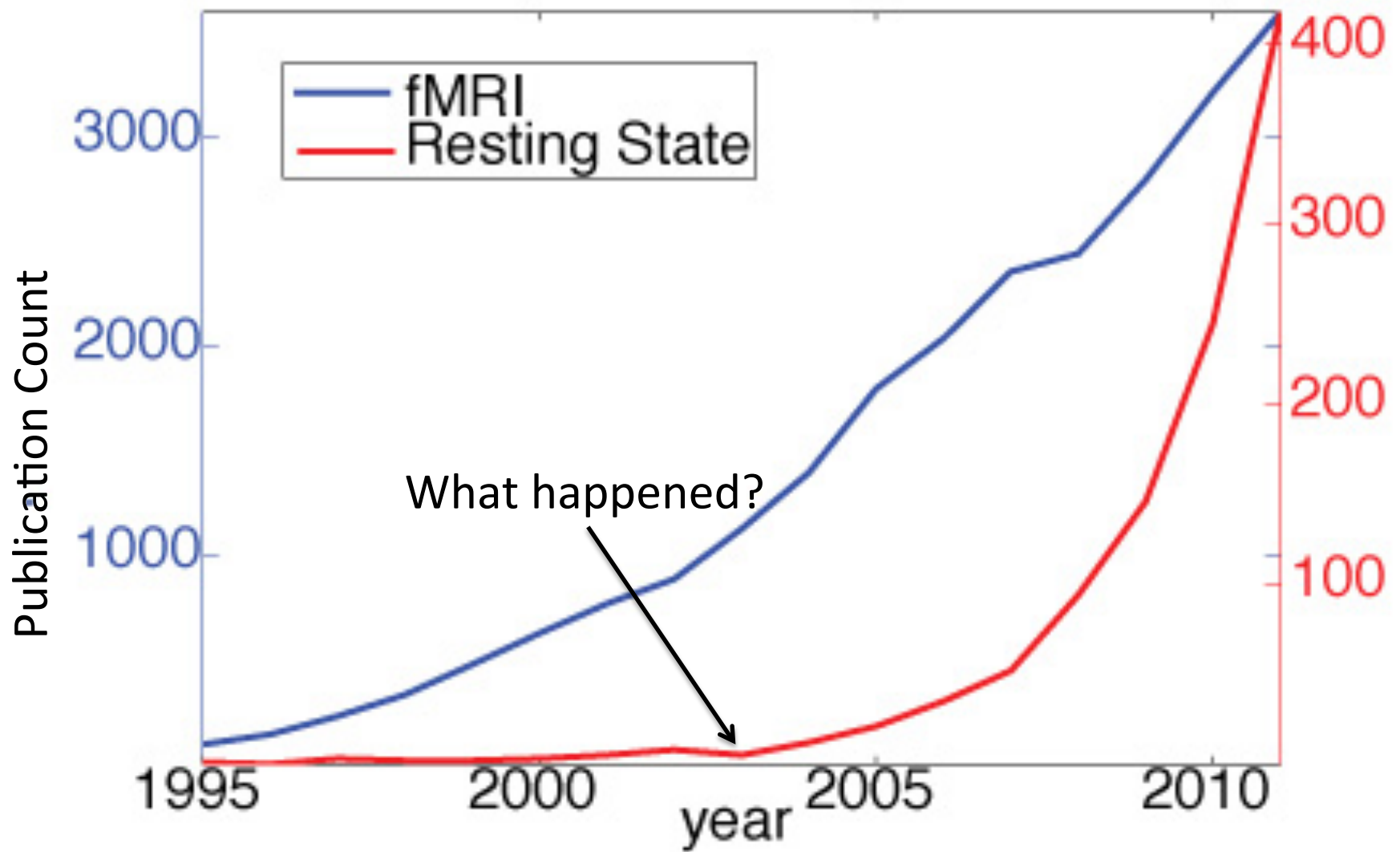


Correlations with “seed  
voxel” in motor cortex  
**during rest**

*B. Biswal et al., MRM, 34:537 (1995)*

Task-based significance shows how brain regions respond  
Connectivity shows how brain regions interact.

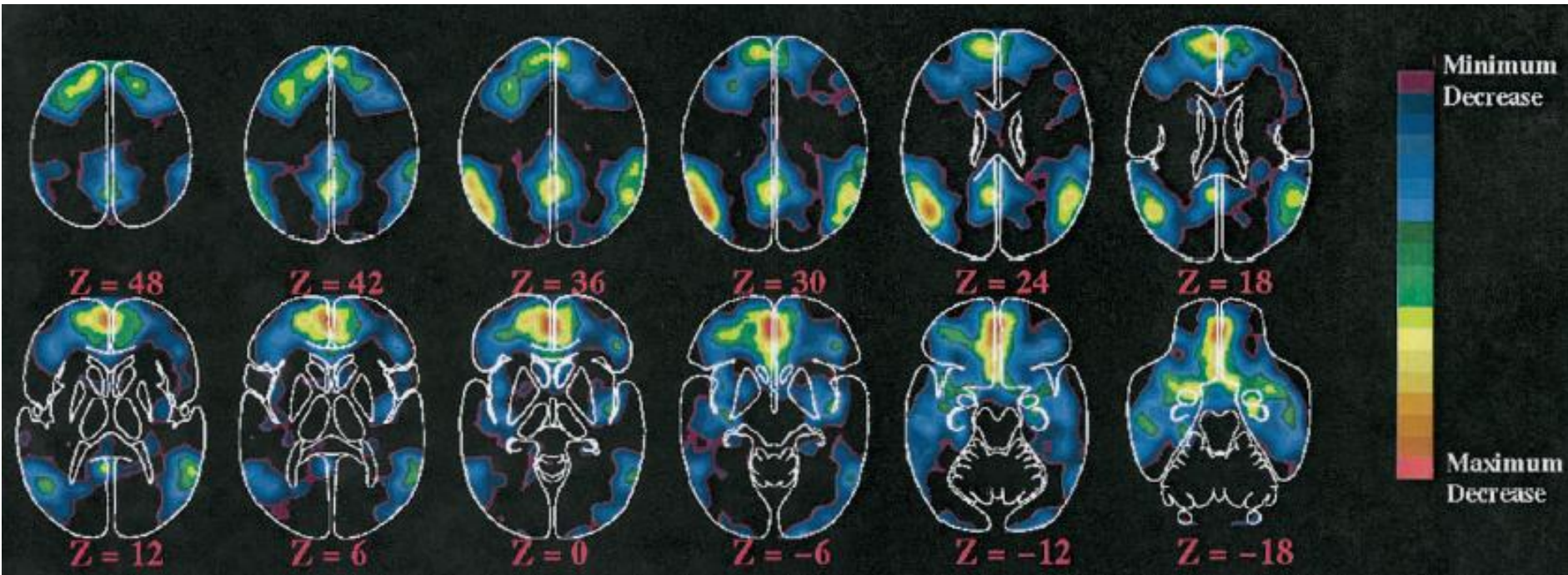
# fMRI and resting state publications



What happened?

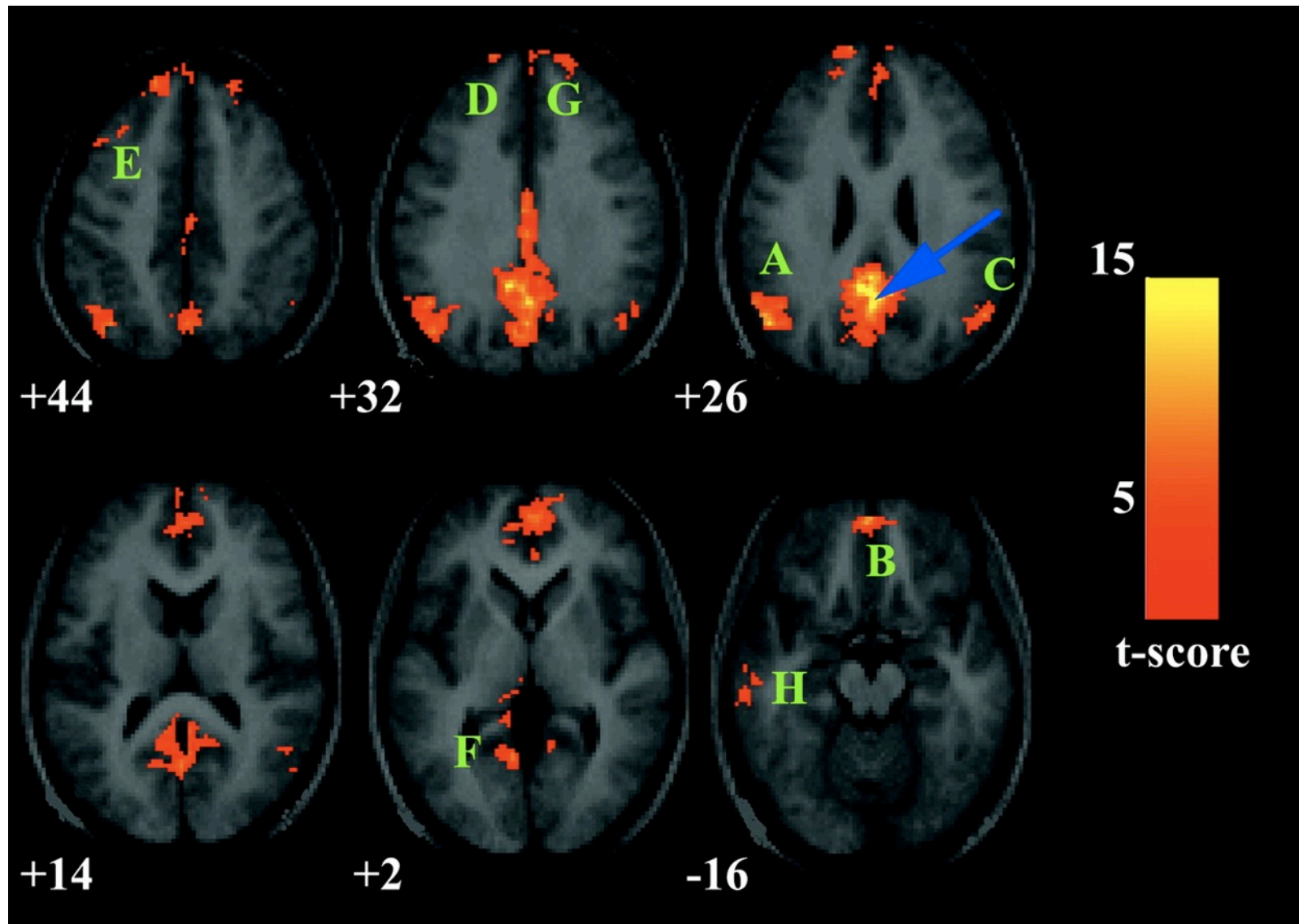
fMRI from PubMed. Resting state from a curated list by a Child Mind Institute Librarian  
Data provided by Matthew Doherty of CMI

# The Default Mode Network



For many tasks, a common group of brain areas shows more activation in the “rest” compared to the task condition.

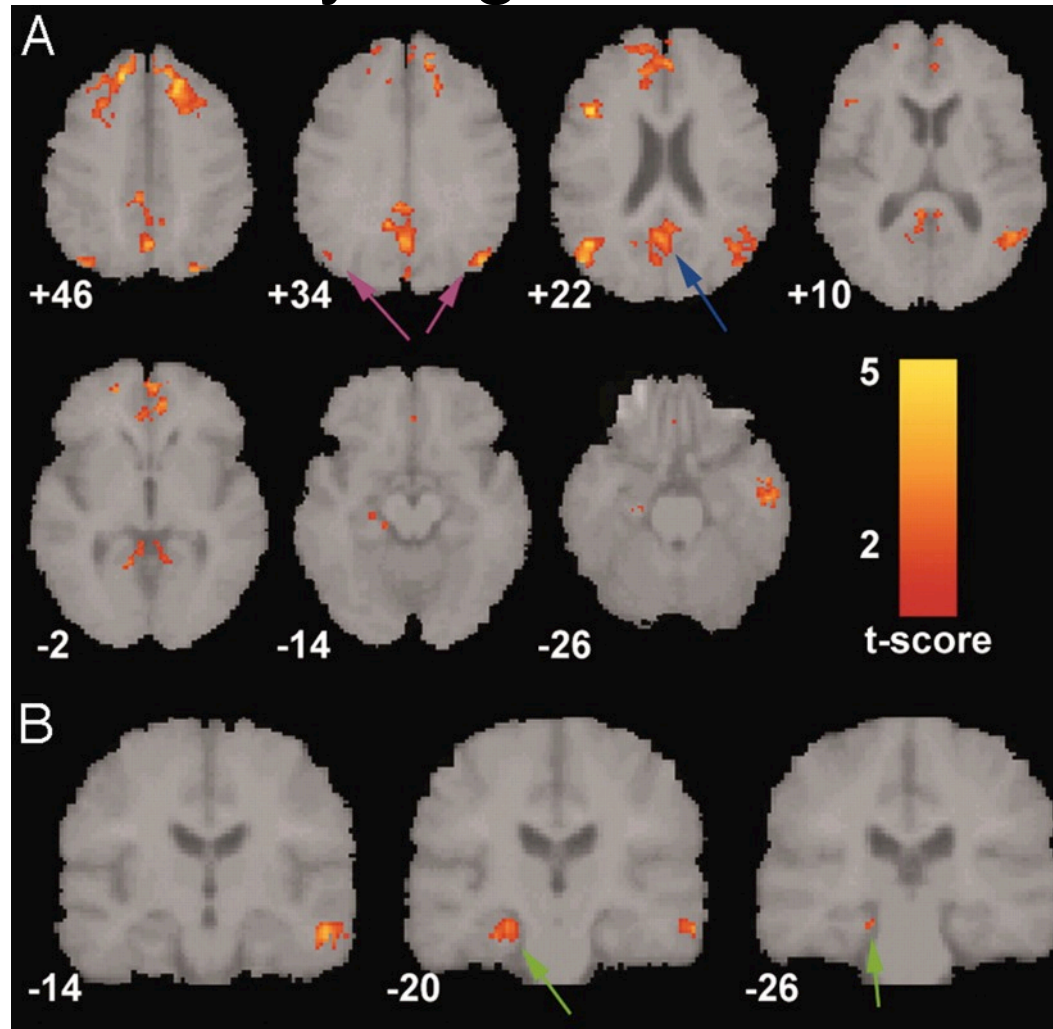
# The Default Mode Network



Default mode regions show significant temporal correlations using fMRI



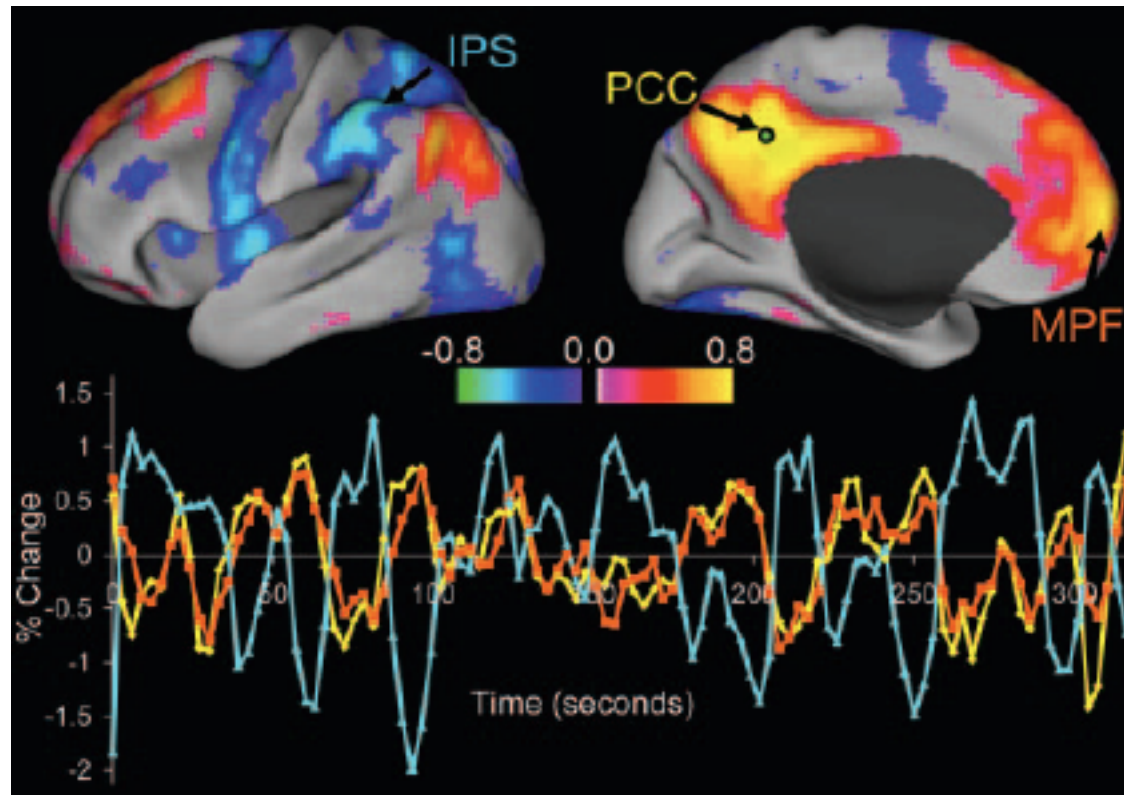
# Resting connectivity might have clinical relevance



Default mode brain regions distinguish  
Alzheimer's Disease patients from healthy elderly

# Big new visions of the brain organization

The human brain is intrinsically organized into dynamic, anticorrelated functional networks



Fox et al, *PNAS* 102, 2005

# This is exciting!!!

No need for tasks!

No need to worry if your volunteer performs the task!

Just throw someone in the scanner and tell them to sit still for 5 minutes!

Get any brain networks you want to study!

People will get Neuro or Psych PhDs without ever running task-based experiments!  
(This has probably already happened)

# fMRI for Epidemiology is Practical

- **ADHD-200:** 491 typically developing (TD) and 285 ADHD children's resting scans from 8 sites  
[http://fcon\\_1000.projects.nitrc.org/indi/adhd200/index.html](http://fcon_1000.projects.nitrc.org/indi/adhd200/index.html)
- **ABIDE:** 573 TD and 539 Autism Spectrum Disorder children's resting scans from 16 sites  
[http://fcon\\_1000.projects.nitrc.org/indi/abide/](http://fcon_1000.projects.nitrc.org/indi/abide/)
- **Nathan Kline Institute Enhanced Rockland Sample**  
Randomly selected large age-spectrum sample (1000+ people) from a NY county is being collected & rapidly shared  
[http://fcon\\_1000.projects.nitrc.org/indi/enhanced/](http://fcon_1000.projects.nitrc.org/indi/enhanced/)



# Is it really THAT exciting?

What are the challenges?

Really. What are they?

Did you think this was going to be another list of bullet points answering this question?

# Some challenges

What exactly do we collect?

Trying to isolate the neural signal  
(Attend Catie Chang's and Steve Gotts' talks)

How do we know the remaining signal is neural?

Method Selection & Applications when everything  
looks good and there are few definitively correct  
results

# What do we collect?

## What is “resting state”?

Awake/Asleep?

Eyes open/closed?

Lighting in room?

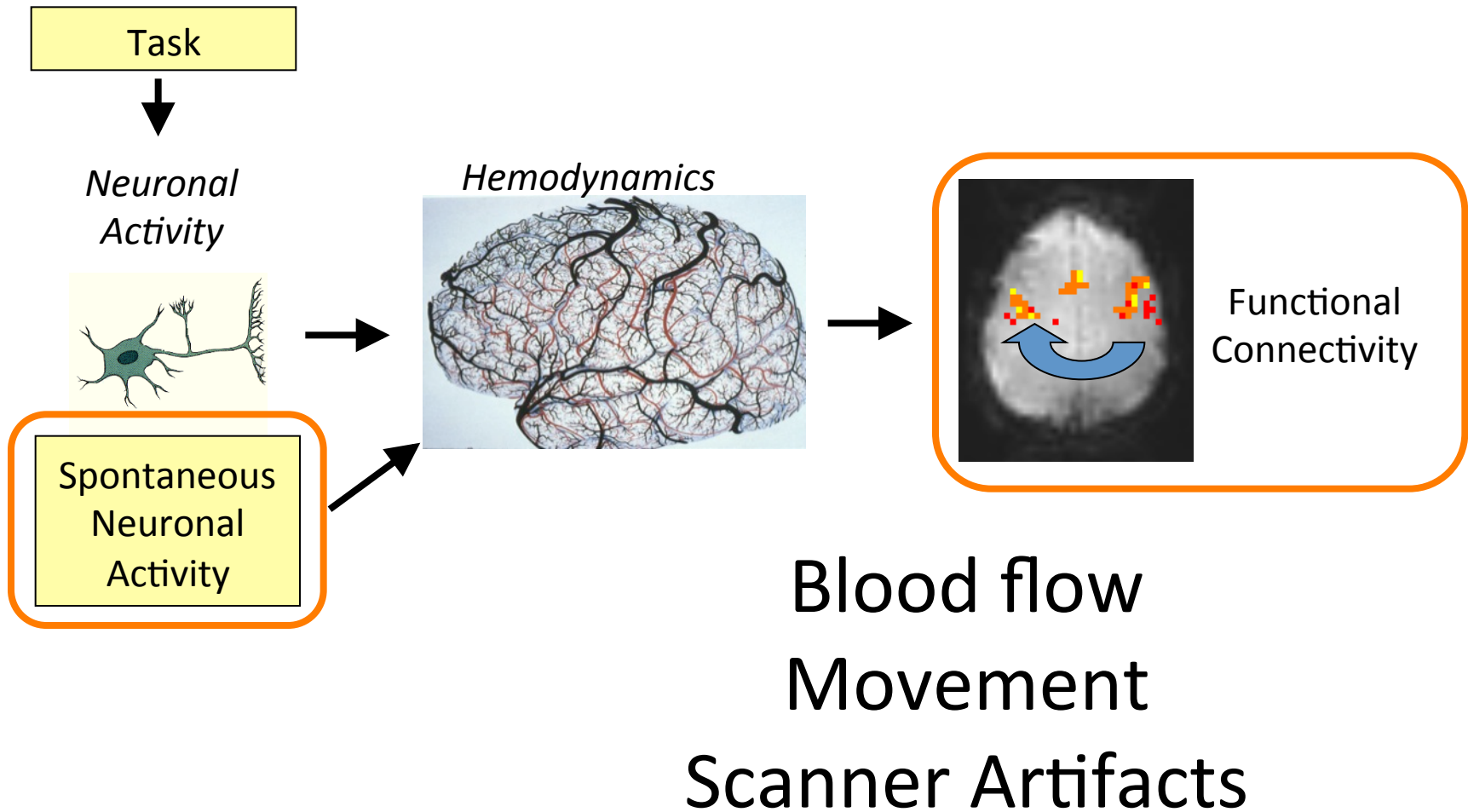
Low level tasks?

## What do you tell the volunteer not to do?

# What do we collect?

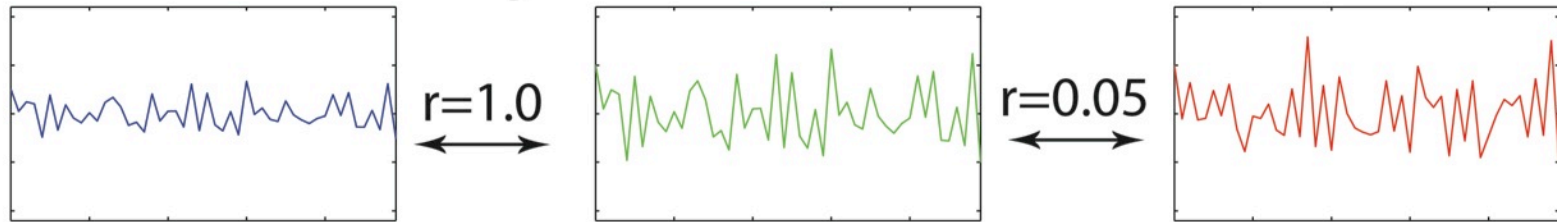
- How long to scan?
  - What gives us stable results?
  - Are the instabilities interesting (connectivity dynamics)?
- How much do scanning parameters matter?
  - Voxel size, in-slice acceleration, flip angle, TR, TE, ...
- When to scan?
  - Time of day
  - Preceding activities
- What can alter results?
  - How can we increase confidence that population differences are neural?

# Isolating the neural signal

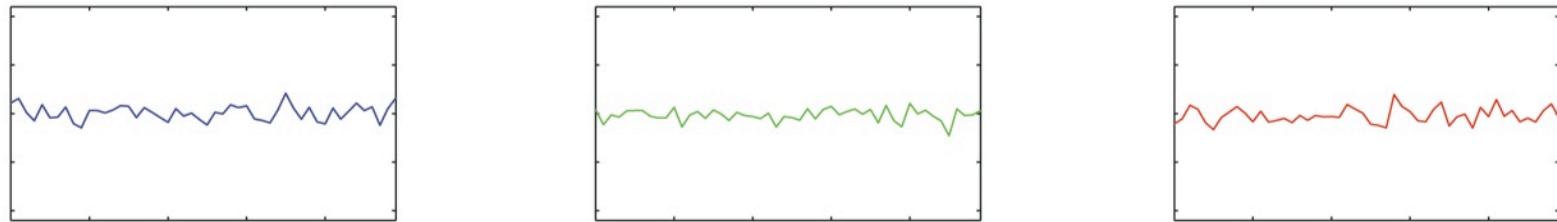


# Isolating the neural signal

Original "neuronal" time series

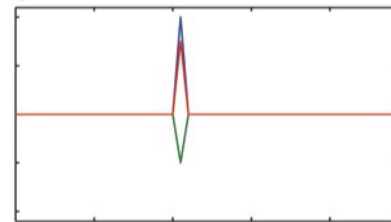
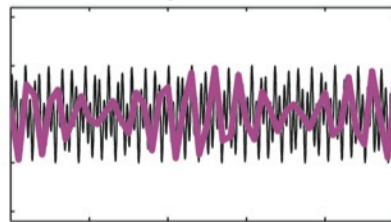


Scanner based noise

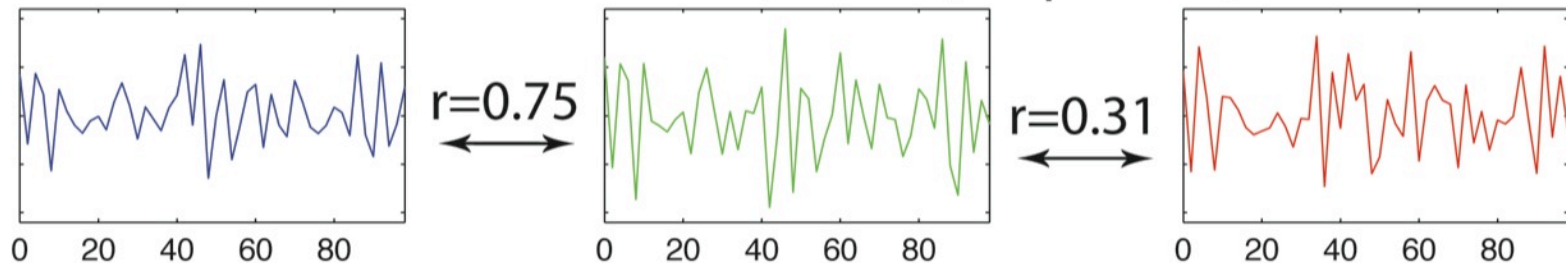


Cardiac and Respiration Noise

Noise spike from head motion



Neuronal time series + scanner, cardiac, respiration, & motion noise

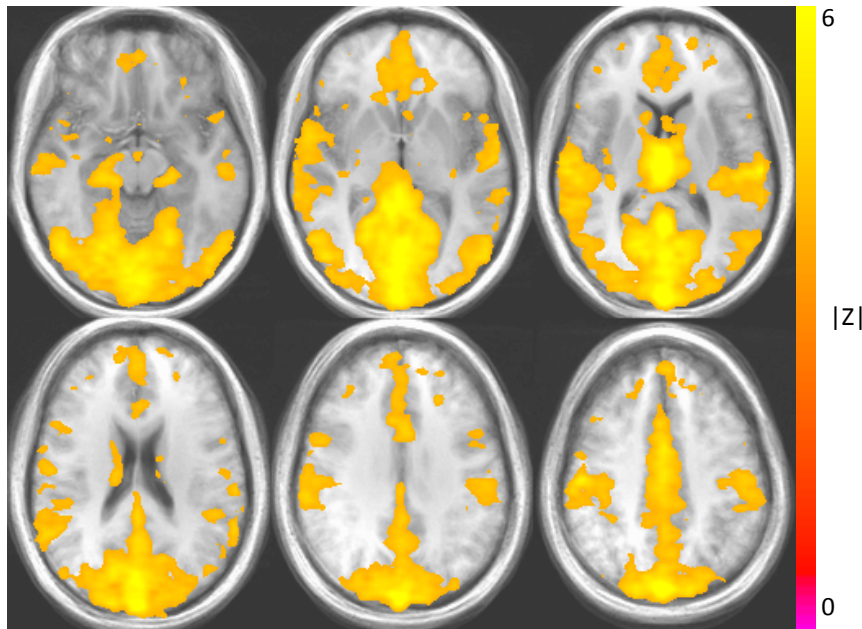


Seconds

fMRI Signal Change

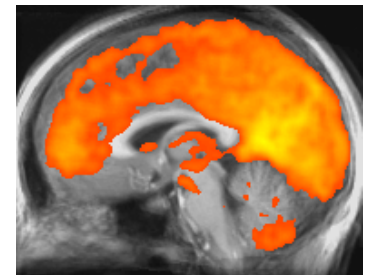
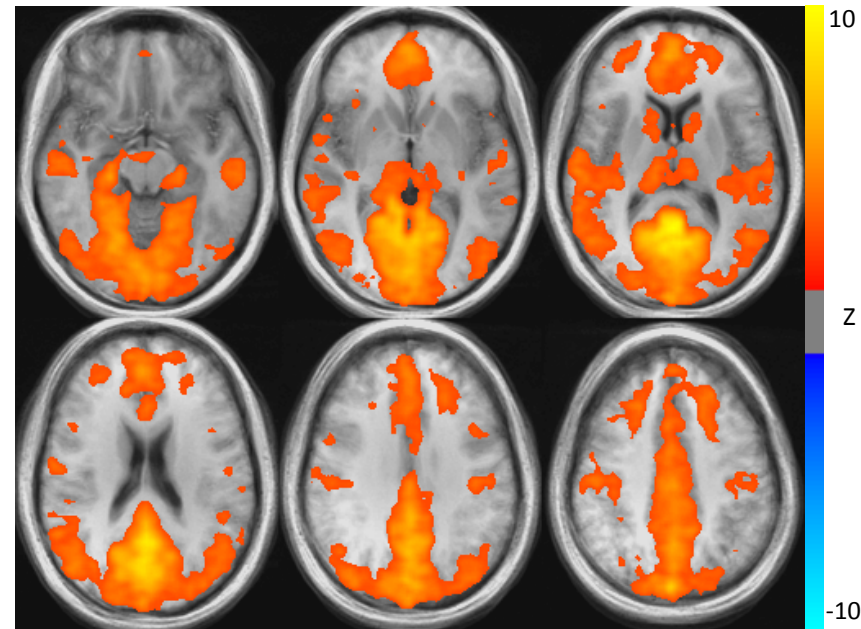
At best respiration and cardiac pulsation adds noise to regional connections. At worst it obscures neural connections.

Respiration changes using RVT



Group ( $n=10$ )

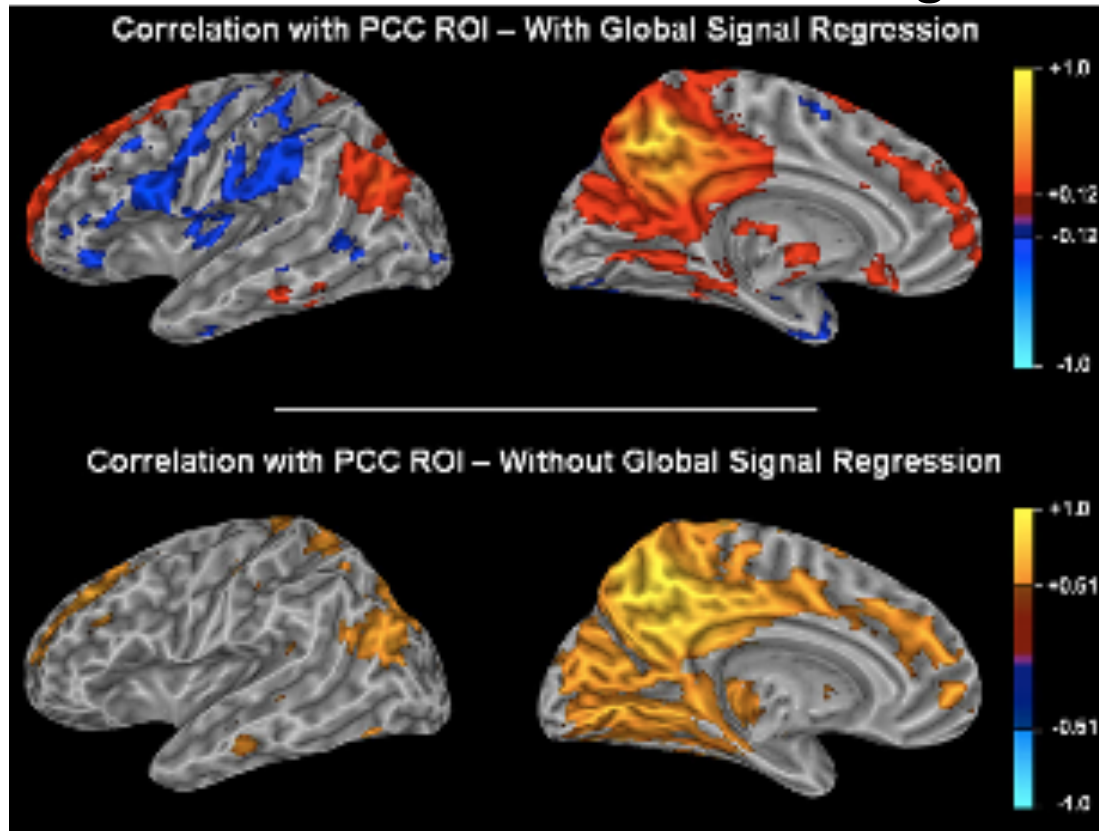
Correlation (of PCC) at Rest



RVT = measuring and tracing (Respiration Volume)/time and removing it from the time series

# Anticorrelated networks are largely an artifact of a preprocessing decision

Correlations to the Posterior Cingulate



Murphy et al Neuroimage 2009

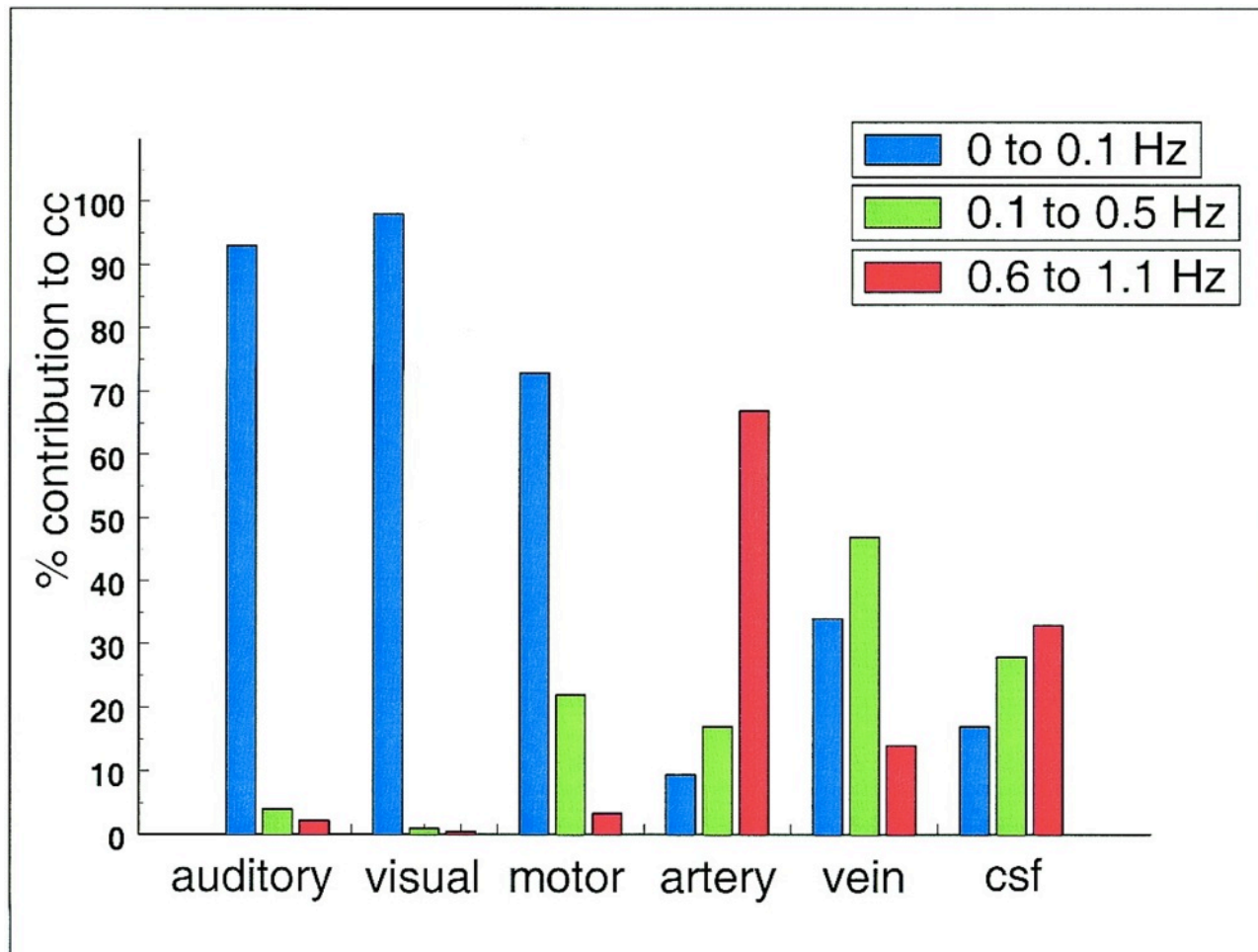
Removing the global signal was supposed to remove non-neural fluctuations, but it also induces anti-correlations

**Removing uncharacterized signals can cause uncharacterized population differences**



# How do we know the remaining stuff is neural?

## Focusing on the low frequencies



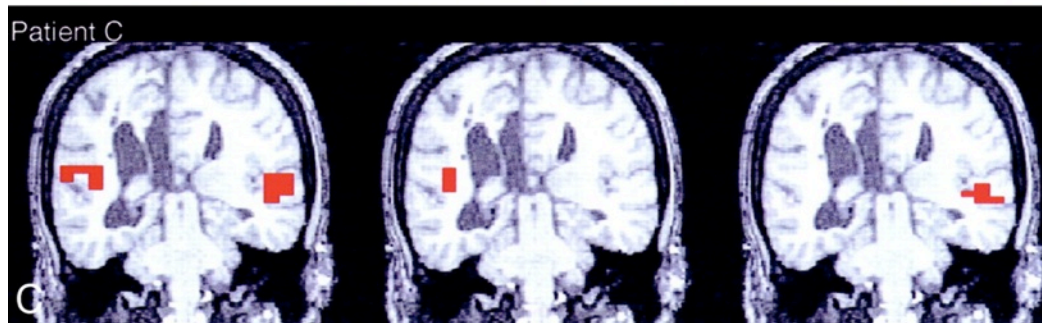
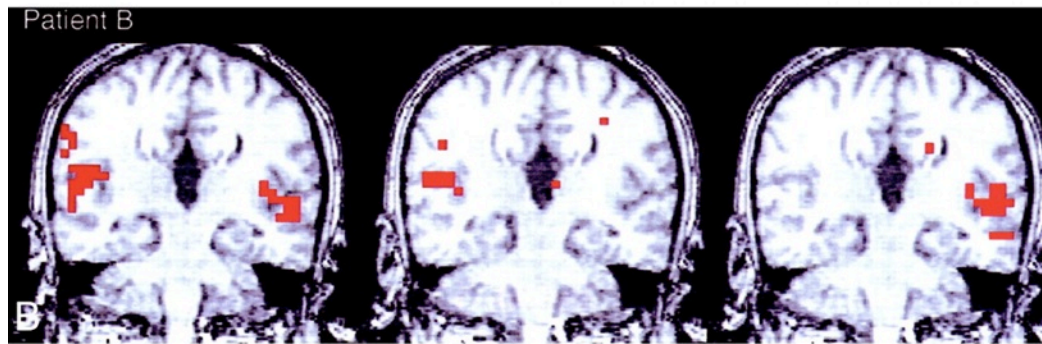
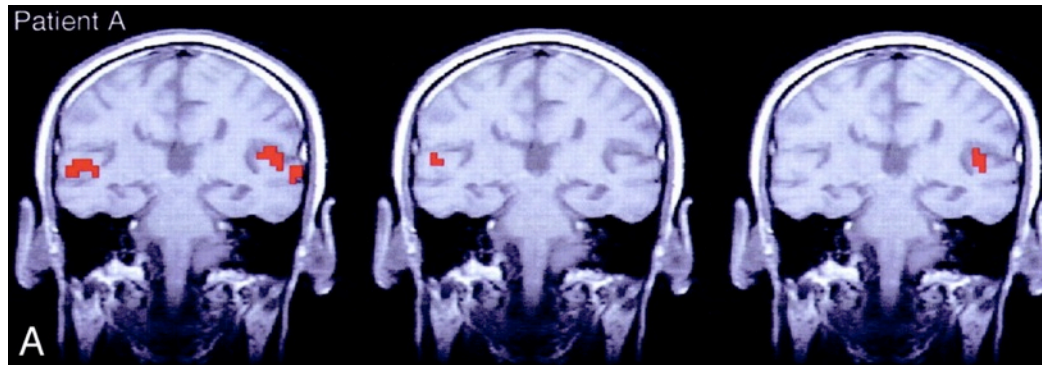
Low frequencies dominate the correlation magnitudes for seeds in the cortex

Anything faster than a hemodynamic (0.3Hz) response is assumed to not be neural

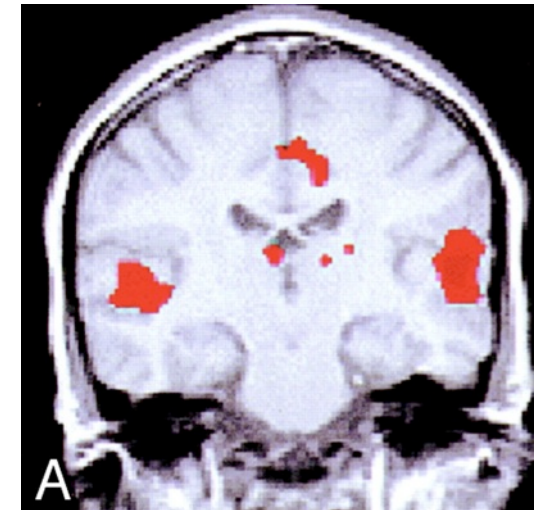
# Aggenesis of the corpus callosum

Activation from a  
text listening task

Right and left auditory  
seeds in resting data



Connectivity map  
from a healthy  
volunteer

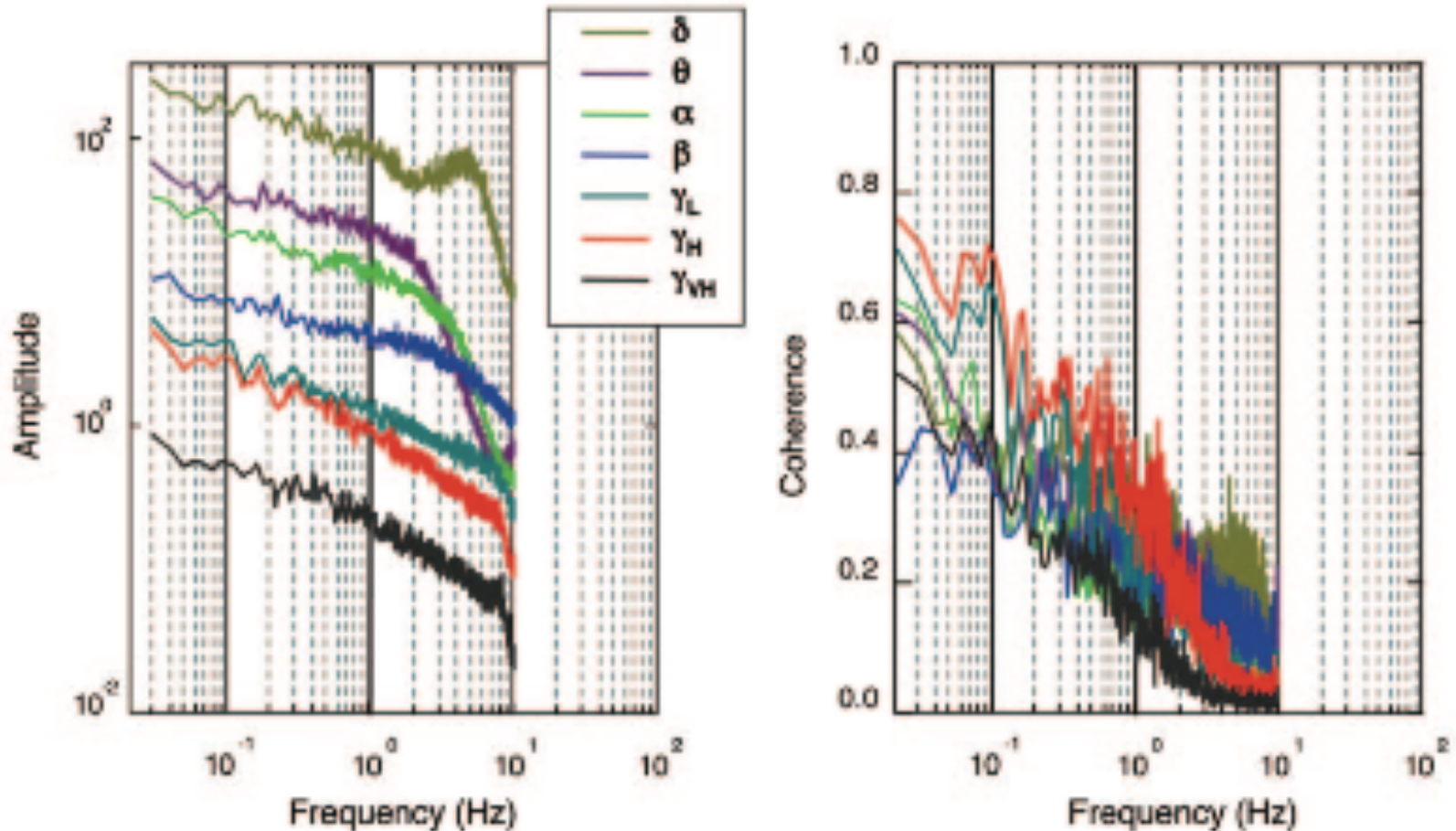


Quigley et al AJNR 2003

An acallosal patient was first  
presented by Lowe et al  
Neuroimage 9:S422 1999

Vasculature is still symmetric, but bilateral neurons are not connected

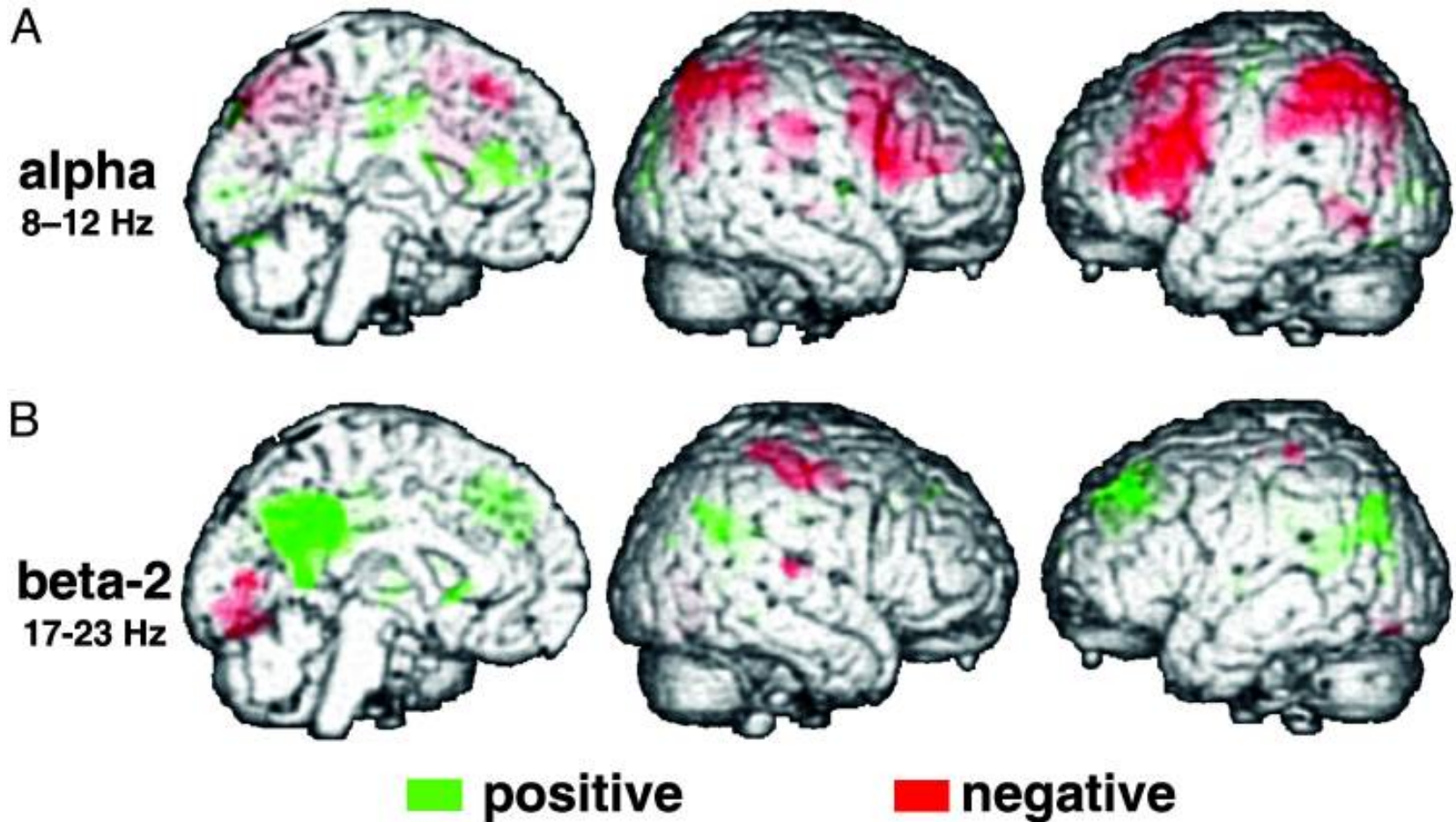
# Electrical Signals can also be slow



There is a high power signal and a coherence across electrodes in multiple LFP frequency bands.



# Relationship to EEG

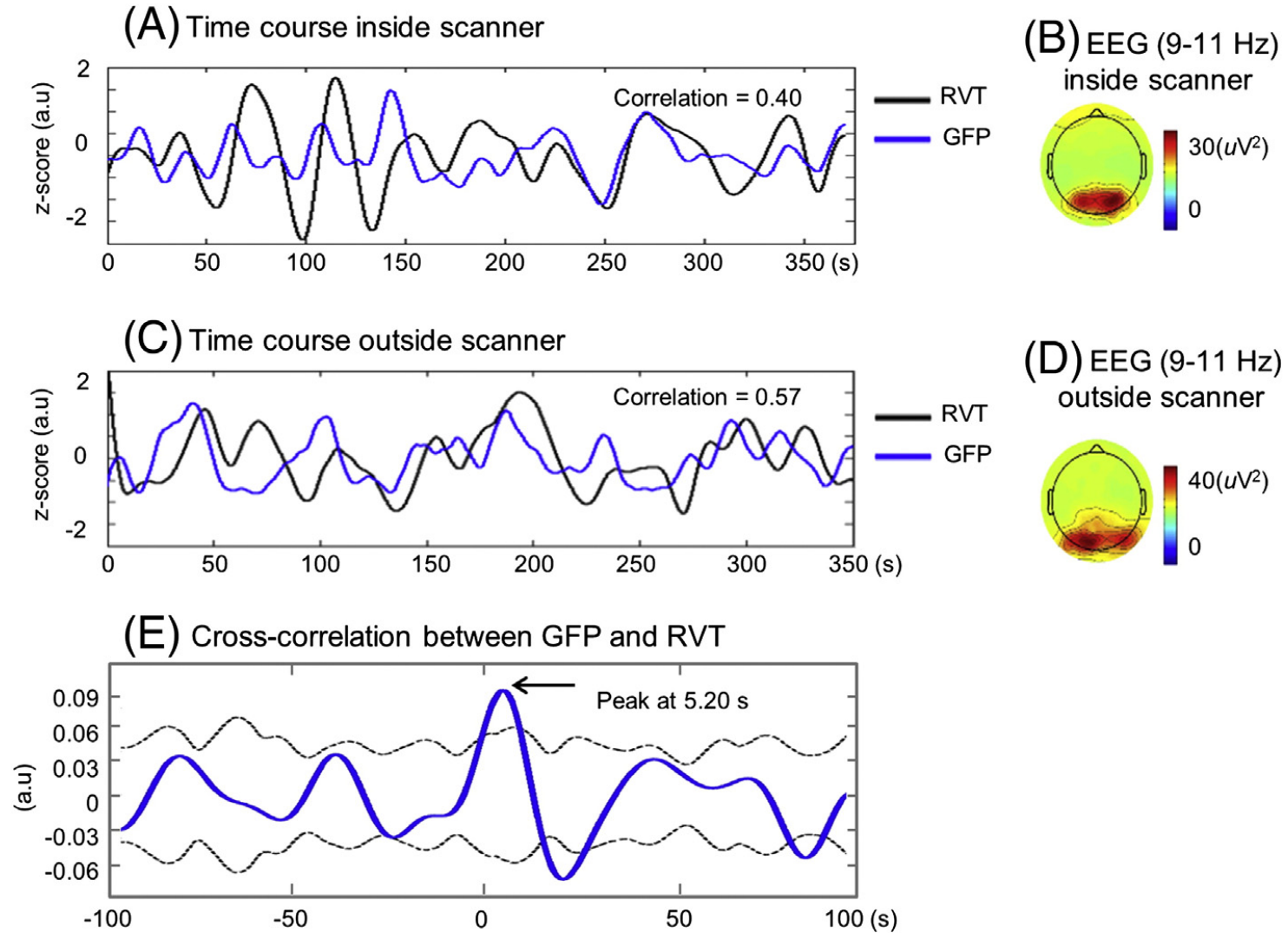


Activation and deactivation maps of EEG signals convolved with a hemodynamic response

Laufs et al PNAS 2003

Catie Chang will talk more about EEG/fMRI

# The EEG/fMRI rest relationship isn't simple

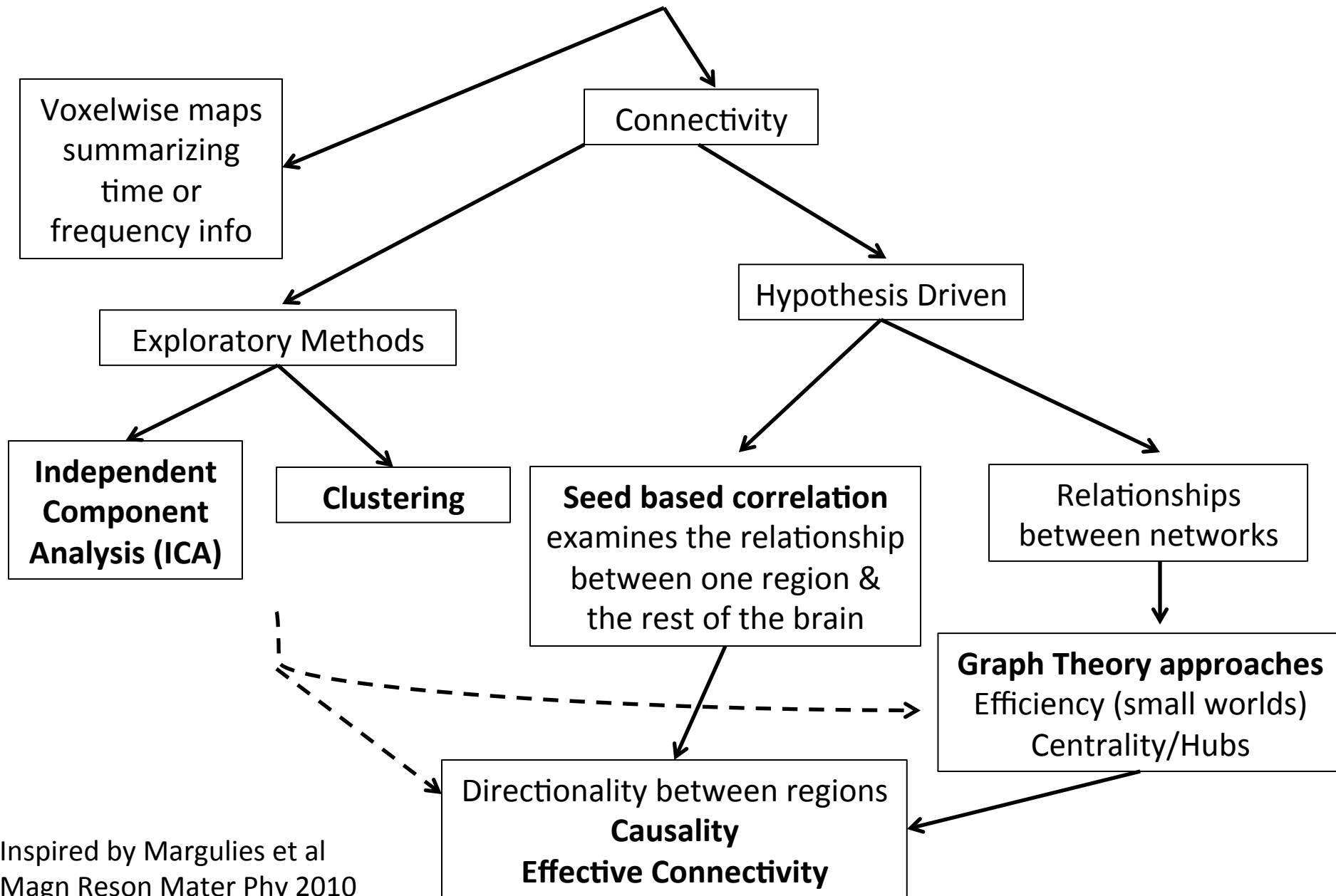


EEG alpha (GFP) also correlates with breathing (RVT)

Yuan, Zotev, Phillips, Bodurka

*Neuroimage*, 2013

# We have our rest fMRI data. Now what?



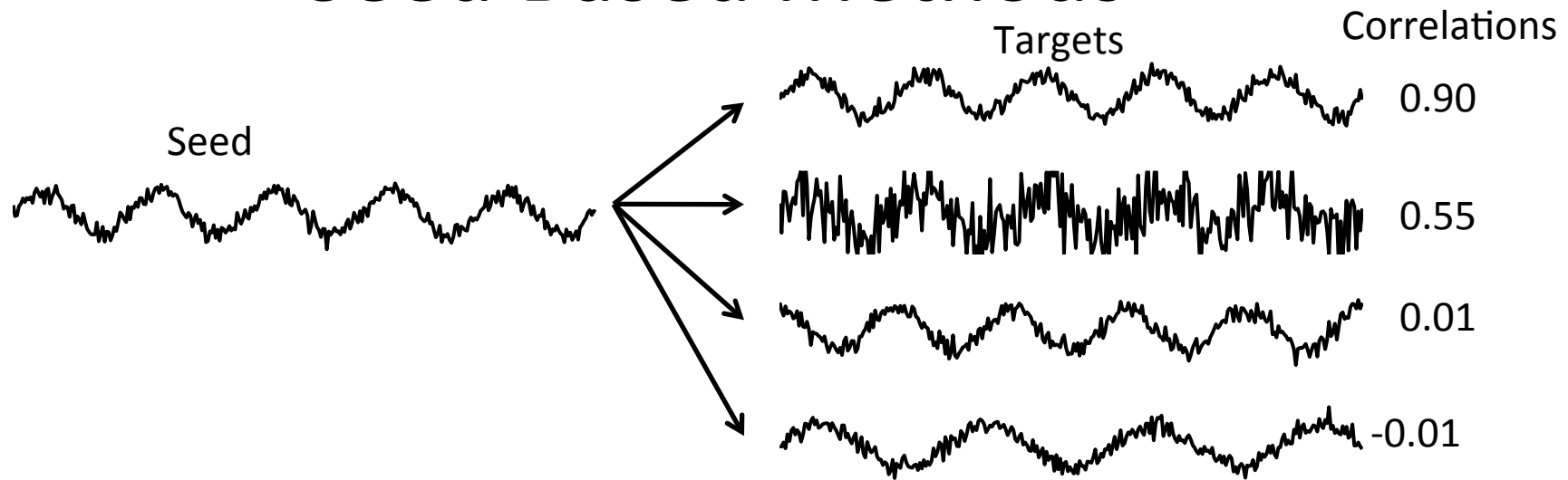
# Methods

At best these methods give us pretty maps of regions that we know have commonalities

- What is normal variation?
- Preprocessing matters
- What differences are statistically significant?
- What differences are reliable and stable across methods?

# Connectivity Analysis tools

## Seed Based Methods



**Find voxels with that have  
similar X to the seed**

Time series shapes

Frequency characteristics

Nonlinear similarities

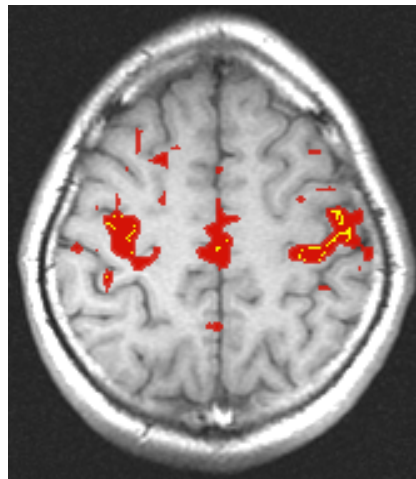
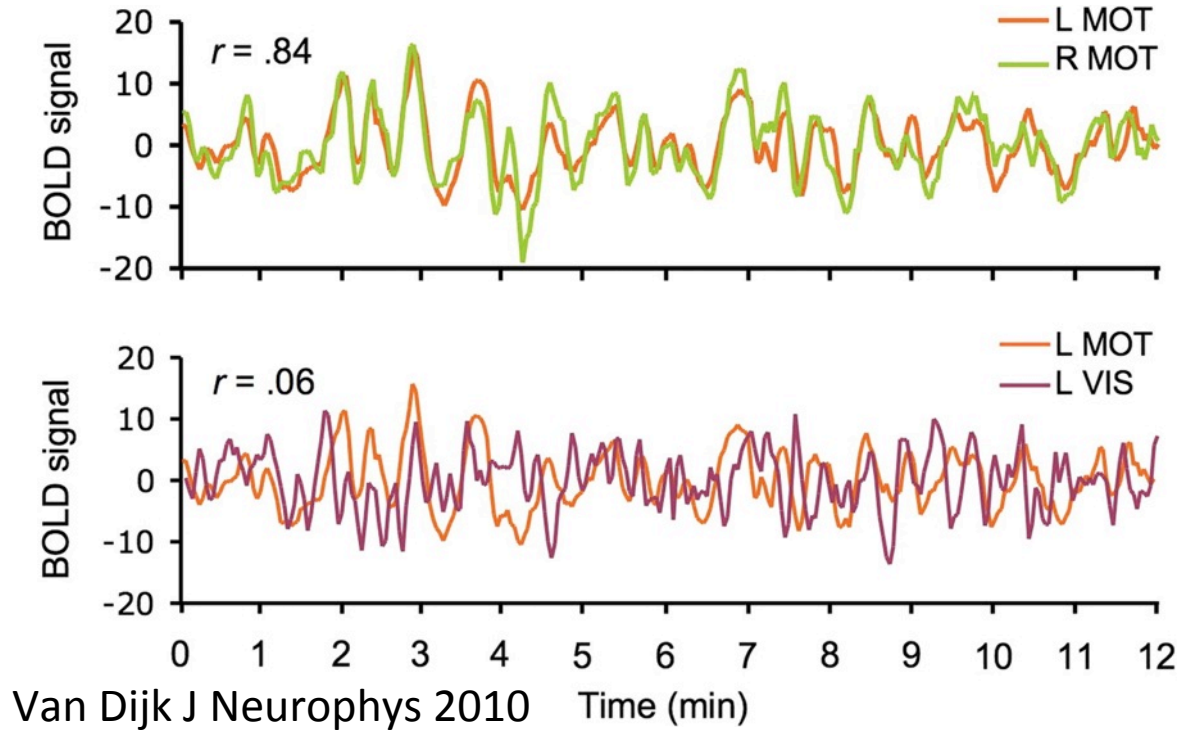
Nonlinear similarities

- Correlation
- Coherence
- Mutual Information
- Causality

Coherence, MI and Causality can also give directionality information (with unclear accuracy)



# Seed Based Methods



***B. Biswal et al., MRM, 34:537 (1995)***

# Advantages of using seeds

- **Hypothesis Driven**

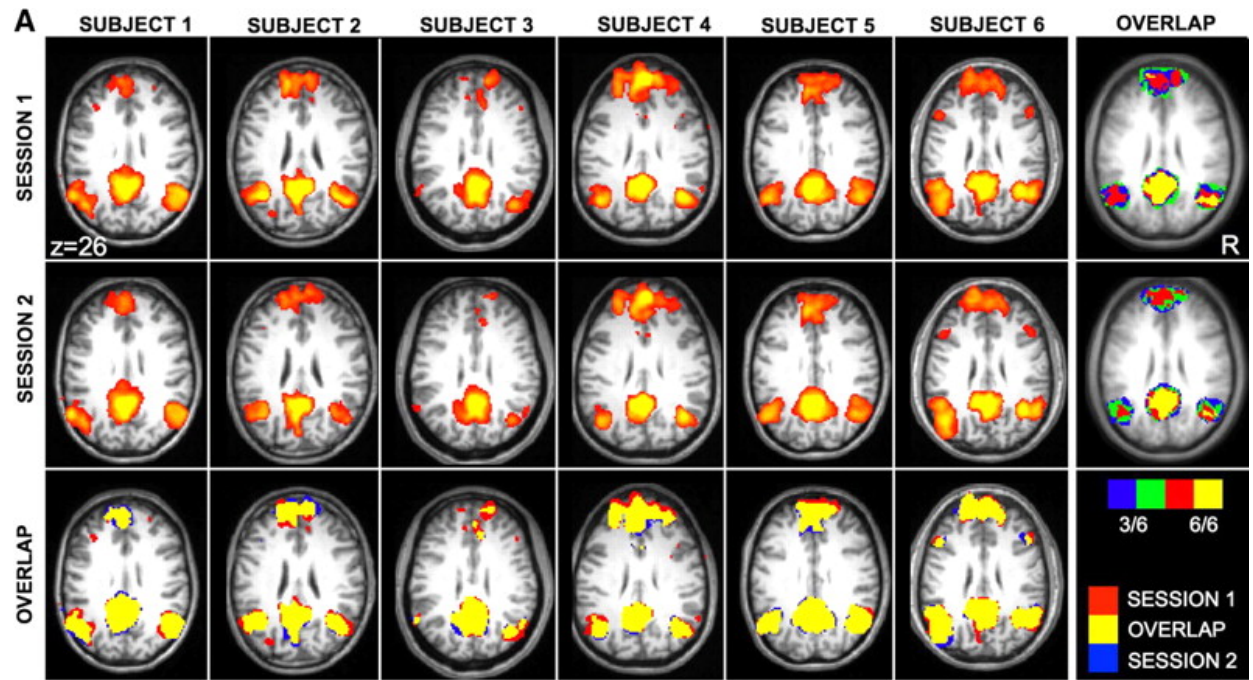
Answers potentially relevant questions:

- What regions are correlated with the seed region?
- How do correlations with the seed region change across populations or after an intervention?

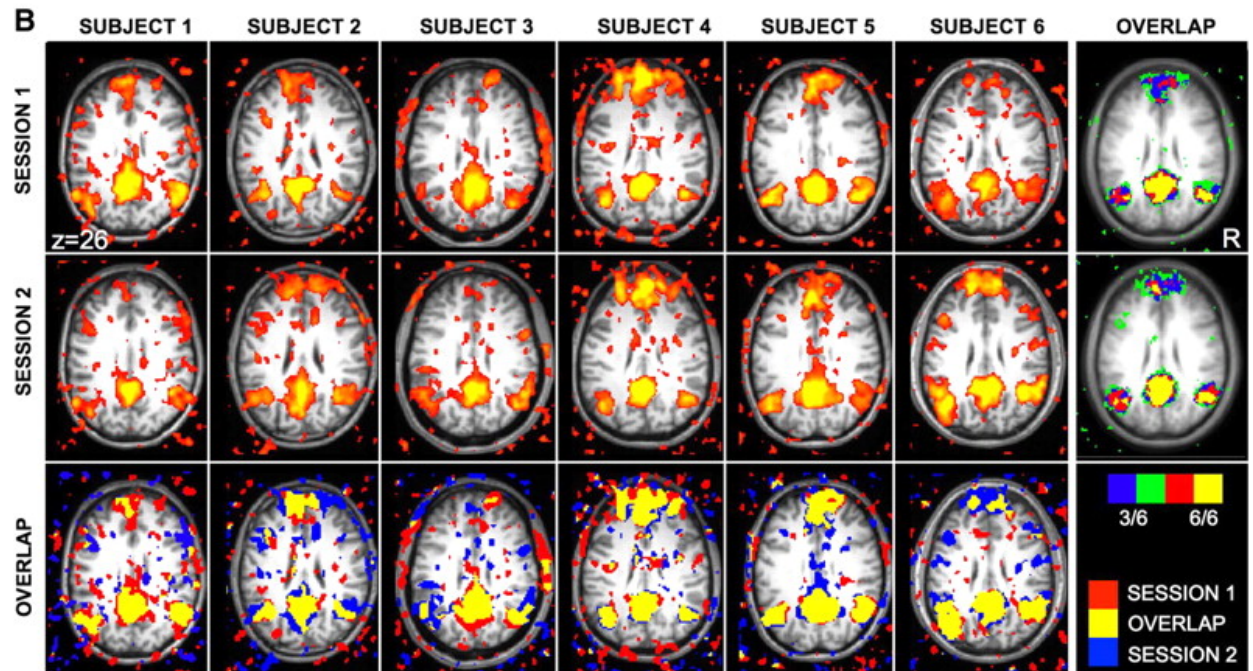
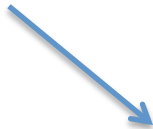
- Shown to give fairly reliable and scientifically relevant results
- Conceptually simple and computationally fast (almost instant in AFNI)

# Cross subject and Session Reliability

20 minute sessions



5 minute sessions



Catie Chang's talk will show that things aren't quite this simple

# Seed based group analysis

One fairly standard method

Take the correlation value map from each subject, convert statistics to z scores and calculate voxelwise group statistics

Issues to consider

Spatial normalization

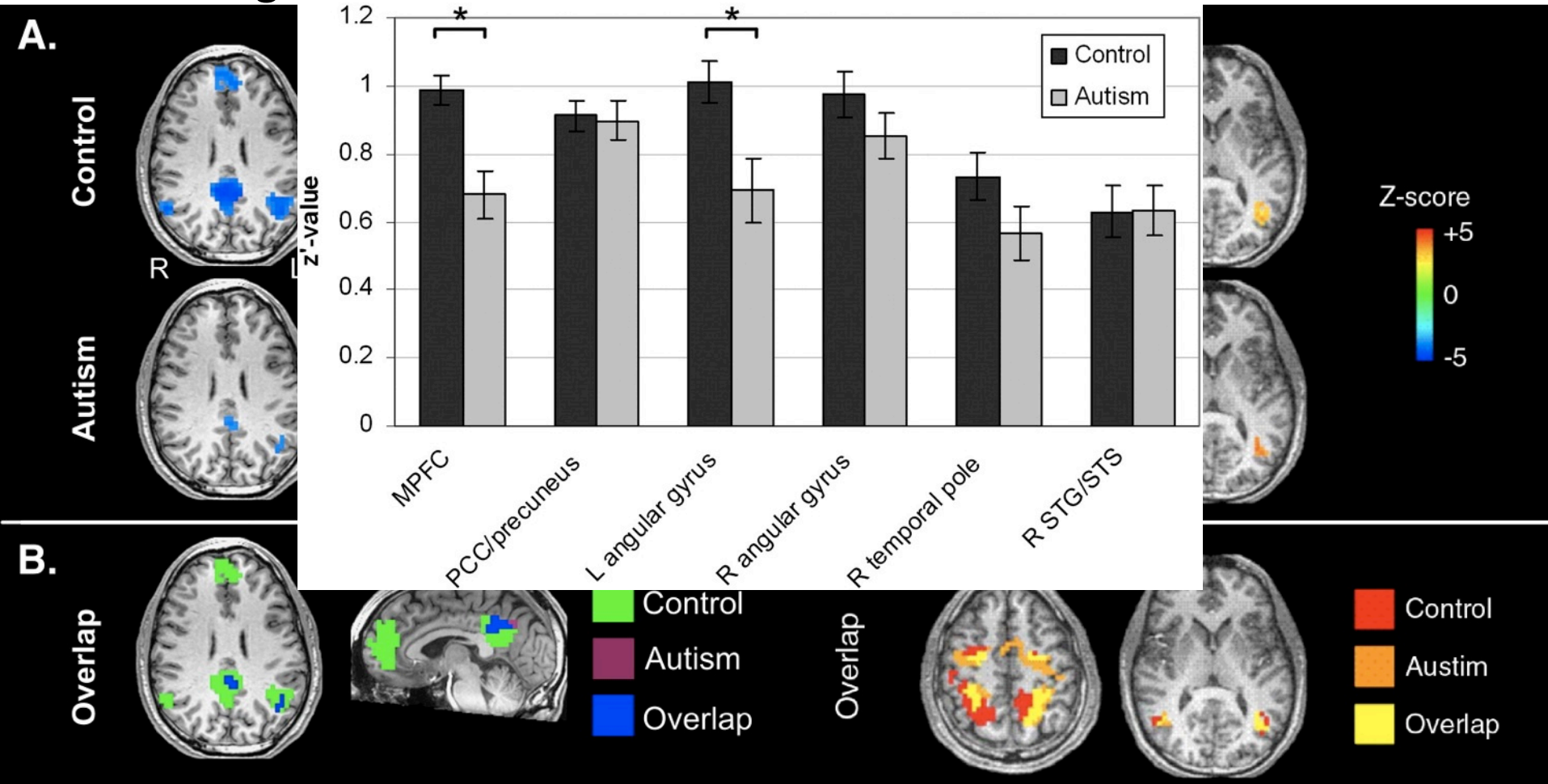
Consistent seed region selection

Watch out for outlier data

# Network changes with Autism

“Task Negative” Network

“Task Positive” Network

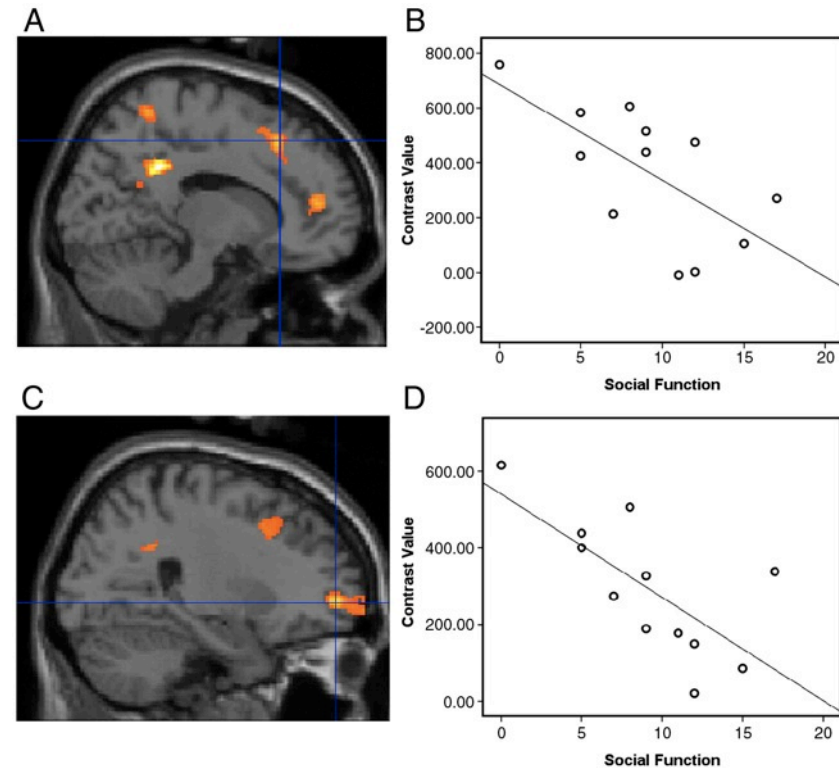




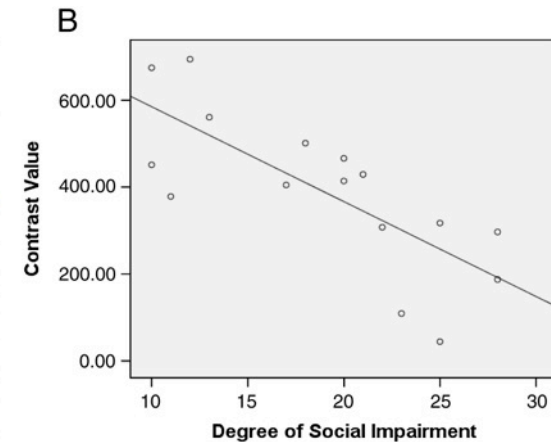
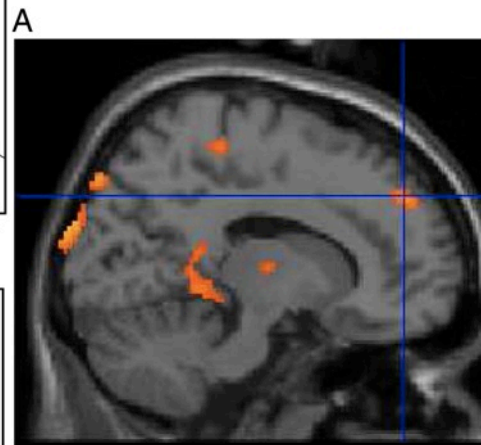
# Connectivity linked to Autistic behavior

Adults

Adolescents



Monk, Peltier, et al,  
Neuroimage 2009



Weng, Wiggins, et al,  
Brain Research, 2010

Significant relationships in the Superior frontal gyrus

*(Analysis Circularity warning)*

# Results are sensitive to processing steps

Data set	Pipeline			FC results ( $p < .05$ , corr.)			Overall pattern
	Seed selection from	Task effects & temporal filtering *	Field of view *	Under-conn. voxels	Over-conn. voxels	Under-connectivity ratio †	
RSVP	TD activation	Task-activated/HP	Whole Brain ROIs only	3563 21	132 0	0.93 1.00	Underconnected Underconnected
		Task-regressed/BP	Whole Brain	708	798	-0.06	Mixed
	ASD activation	Task-activated/HP	Whole Brain ROIs only	2073 5	176 3	0.84 0.25	Underconnected Mostly underconnected
		Task-regressed/BP	Whole Brain	603	1078	-0.28	Mostly overconnected
	Combined activation	Task-activated/HP	Whole Brain ROIs only	3711 14	127 0	0.93 1.00	Underconnected Underconnected
		Task-regressed /BP	Whole Brain	696	833	-0.09	Mixed
	Just et al.	Task-regressed/ BP	Whole Brain	745	976	-0.13	Mixed
VS	TD activation	Task-activated/HP	Whole Brain ROIs only	376 29	2580 0	-0.75 1.00	Overconnected Underconnected
		Task-regressed/BP	Whole Brain	467	934	-0.33	Mostly overconnected
	ASD activation	Task-activated/HP	Whole Brain ROIs only	308 3	3704 2	-0.85 0.20	Overconnected Mixed
		Task-regressed/BP	Whole Brain	518	2012	-0.59	Overconnected
	Combined activation	Task-activated/HP	Whole Brain ROIs only	323 17	2519 2	-0.77 0.79	Overconnected Underconnected
		Task-regressed /BP	Whole Brain	442	1334	-0.50	Overconnected
	Just et al.	Task-regressed/ BP	Whole Brain	87	1900	-0.91	Overconnected
RS	DMN	HP	Whole Brain ROIs only	1076 57	771 1	0.17 0.97	Mixed Underconnected
	DMN	BP	Whole Brain	1403	1076	0.13	Mixed
	Just et al.	BP	Whole Brain	301	2106	-0.75	Overconnected

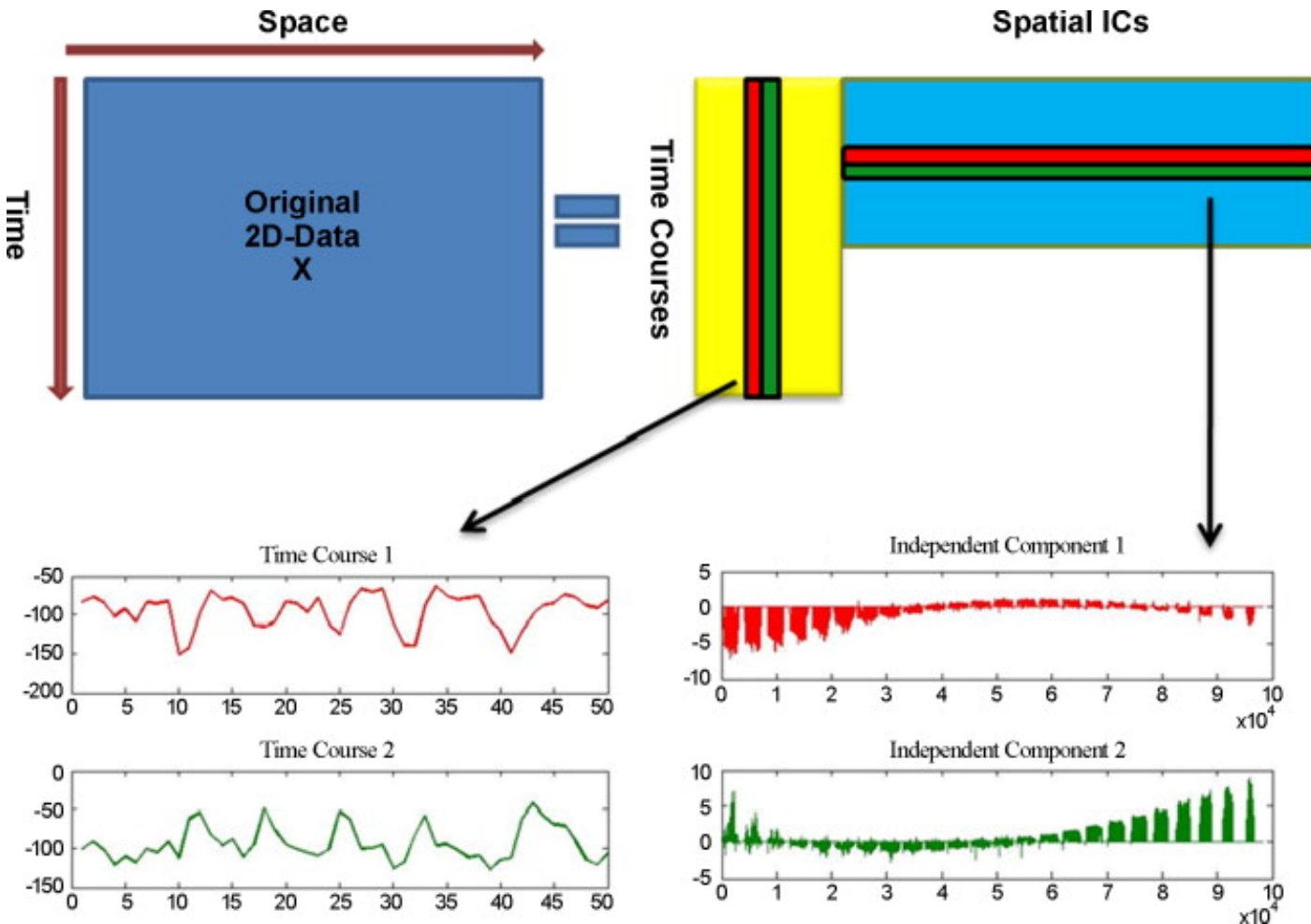
# Disadvantages of using seeds

- Potentially sensitive to seed selection and pre-processing
- After pre-processing, no easy way to distinguish neural from non-neural connections
- Needs a separate seed for every network
- We still don't know what differences are scientifically or clinically meaningful



# Independent Component Analysis

Great for identifying common patterns without making model assumptions or even selecting regions of interest

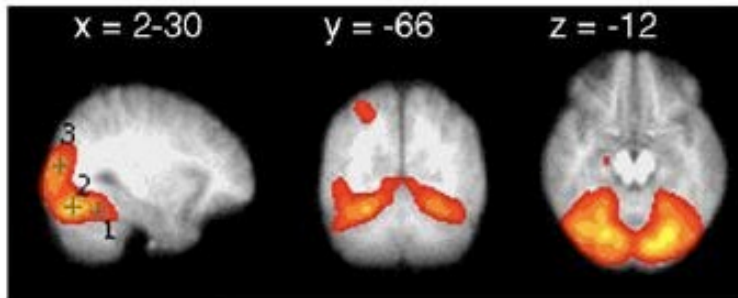


Data is decomposed into a set of spatially independent maps and a set of time courses

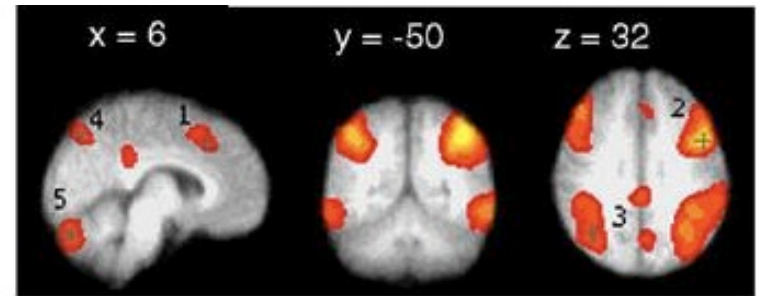
There are multiple methods for identifying relevant components  
Also multiple ways to model groups of volunteers

# 5 brain networks using ICA

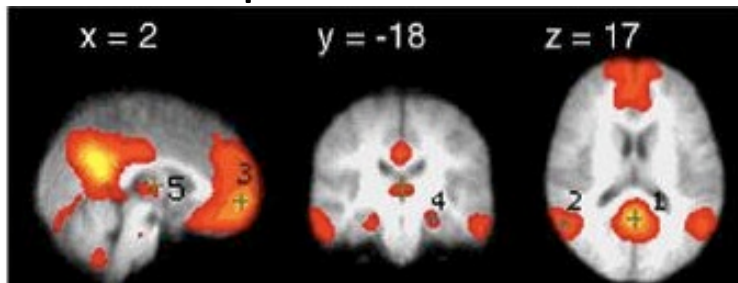
Visual



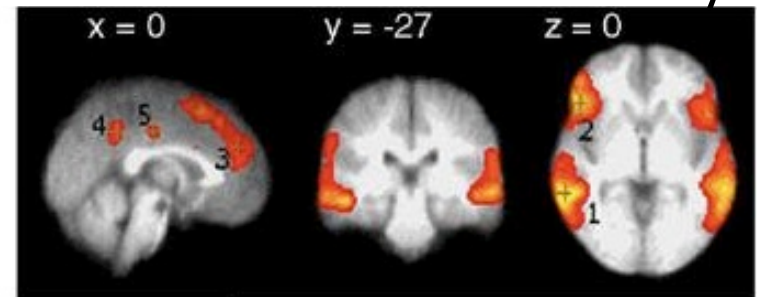
Dorsal “What” Pathway



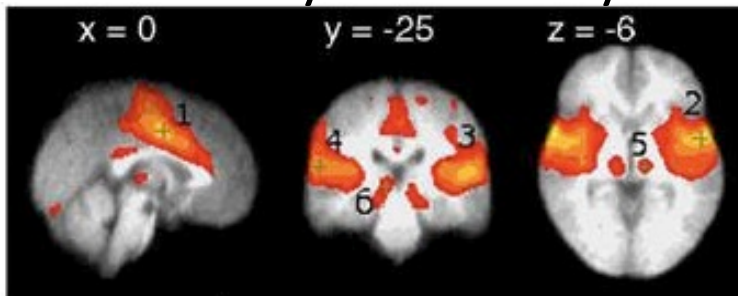
Visuospatial & Executive



Ventral “Where” Pathway



Sensory & Auditory



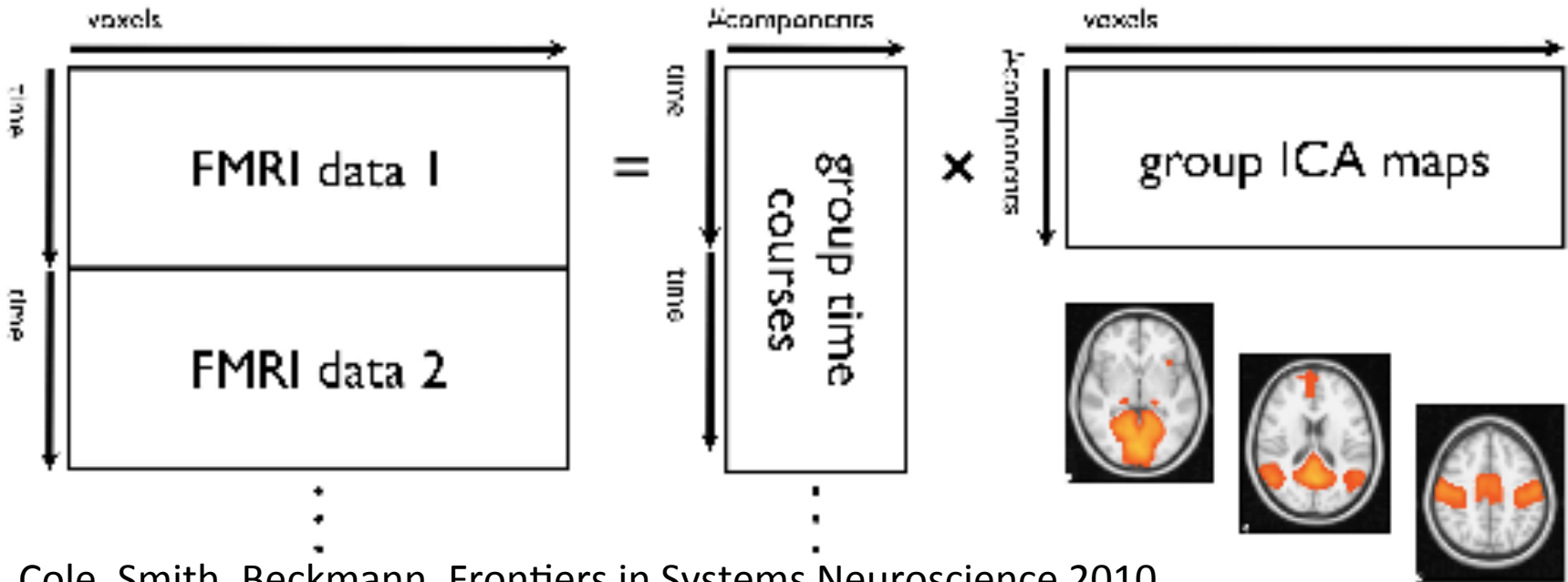
M. De Luca et al., *NeuroImage* 2006

Network names are based on knowledge from past research

# ICA Advantages

- No seed regions
- Everything in the brain is placed in a network
- Can often pull out equipment, respiration and motion artifacts as separate components  
(at least for individual subject ICA)
- Can start without any model of what you expect to see
- Can find something interesting you weren't looking for
- Can be used for noise removal before running other analyses

# One ICA Group Analysis Method



Cole, Smith, Beckmann, Frontiers in Systems Neuroscience 2010

Model the subjects' data as one long time series

The component time series from each subject can also be used to generate subject-specific maps and magnitude values

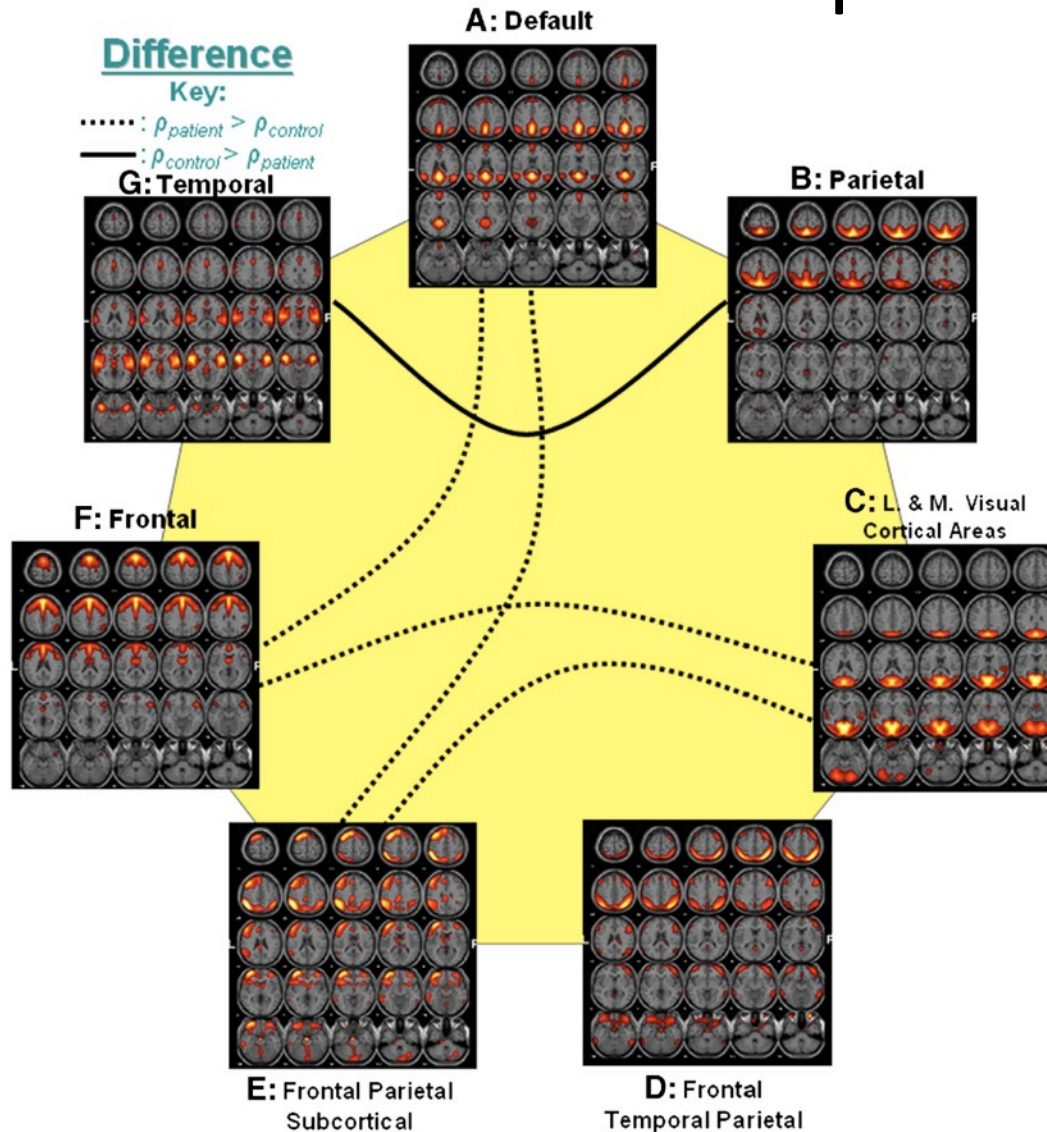
# There are other ICA Group analysis methods

For example you can run ICA on each subject and find ways to align components

gRAICAR Yang et al, Neuroimage 2012

For any approach you still need assumptions of components of interest or use the component times series or spatial maps to identify interesting similarities or differences across groups

# ICA then causality to show differences in Schizophrenia



Identified the same components in the two populations

Looked at how the different components correlated with each other at various lags

Correlations between networks differed between healthy volunteers and patients

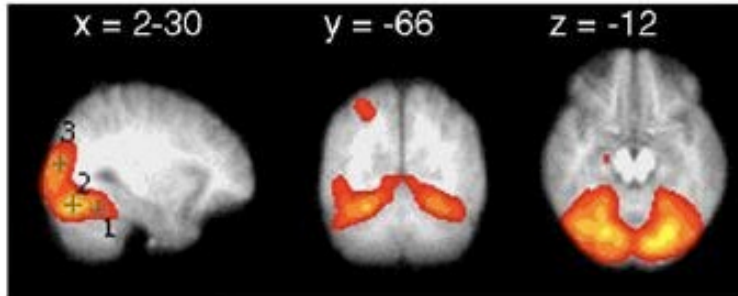


# Limitations of ICA

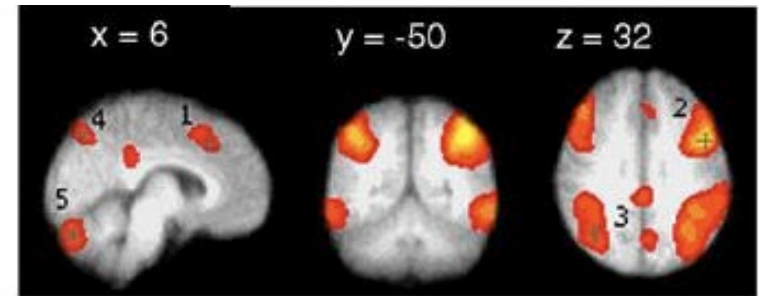
- All we know is that components are independent  
What the #\$%! does that mean?
- While we might observe consistency across a population it isn't a mathematical requirement
- You need to define the # of components & this affects the results
- Calculations are iterative and can vary even with the same data
- There is no order to the components. You always need to set rules on how to identify relevant components and significant voxels

# 5 brain networks using ICA?

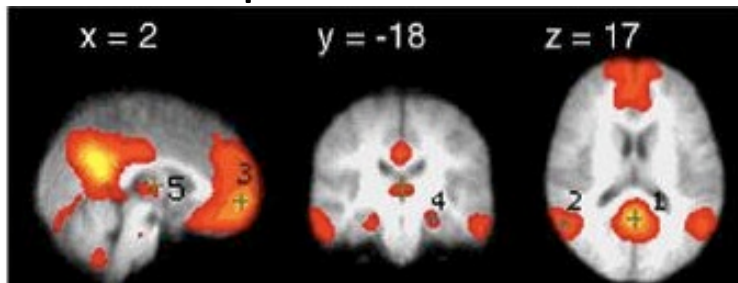
Visual



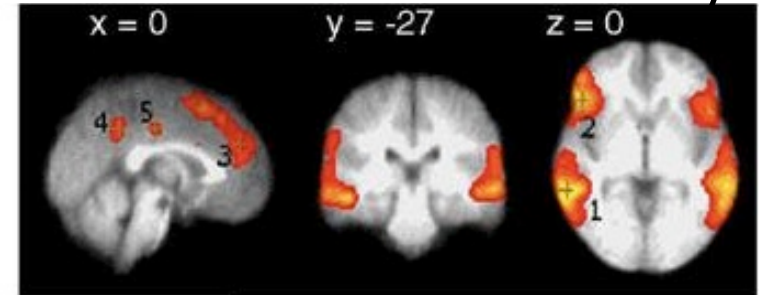
Dorsal “What” Pathway



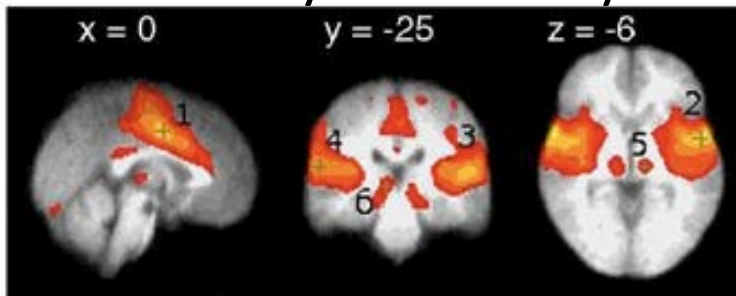
Visuospatial & Executive



Ventral “Where” Pathway

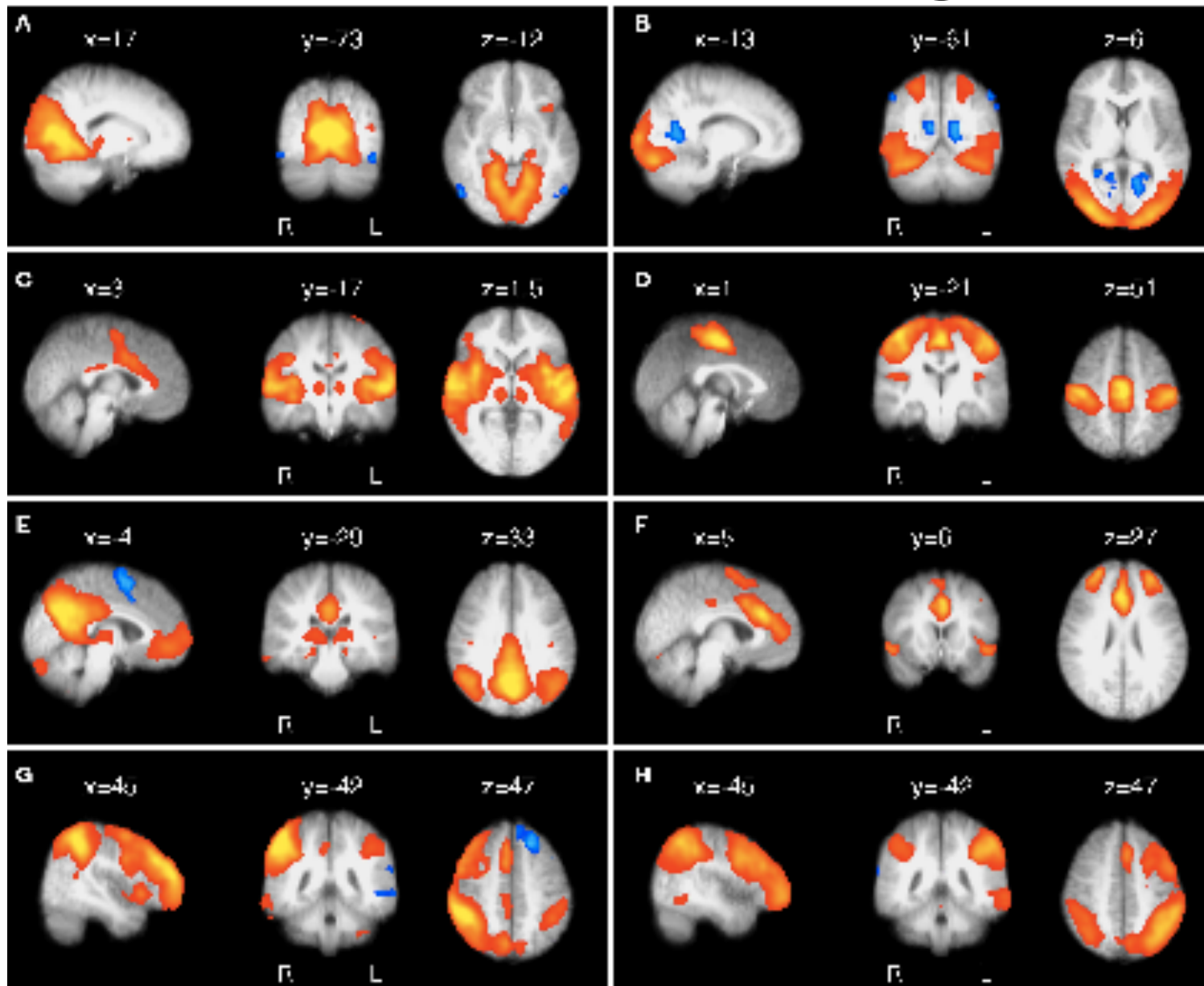


Sensory & Auditory

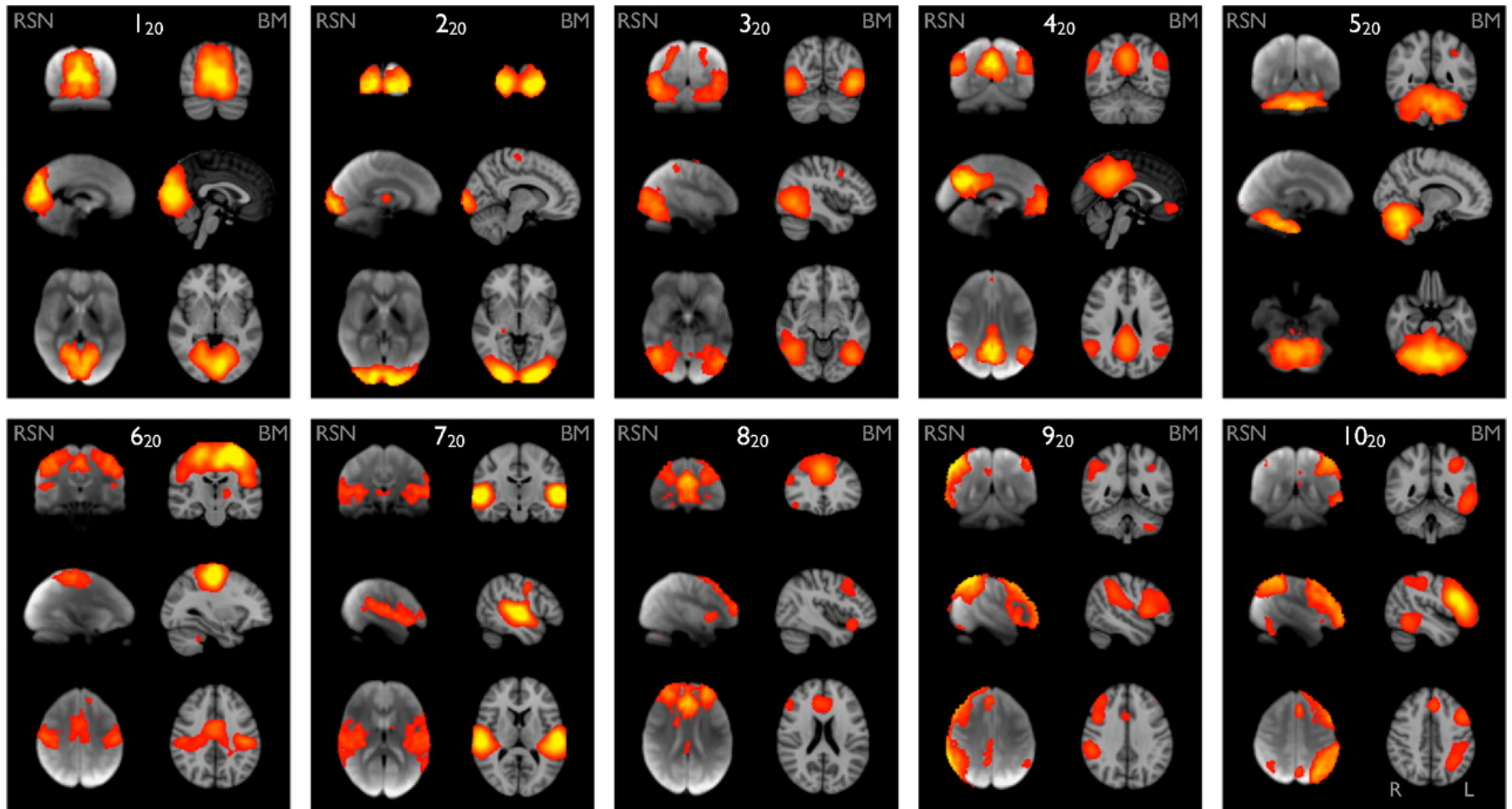


M. De Luca et al., *NeuroImage* 2006

# 8 Brain networks using ICA?

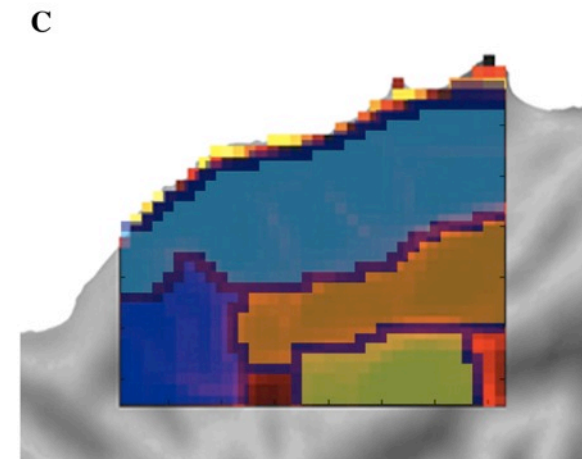
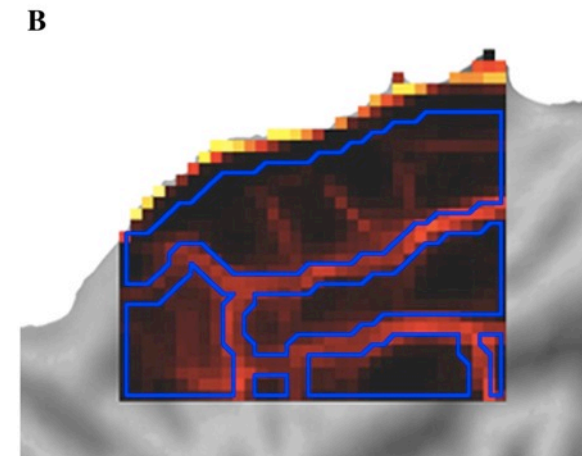
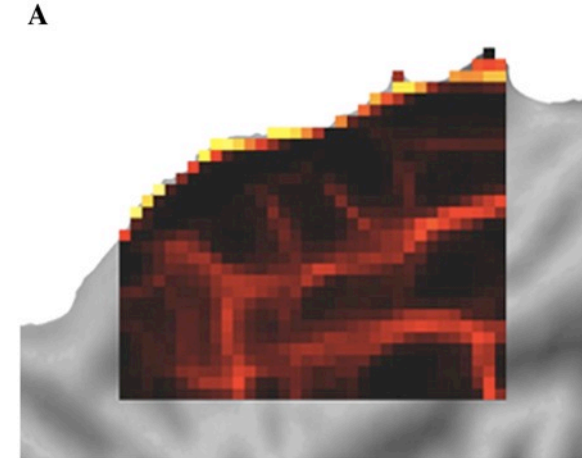
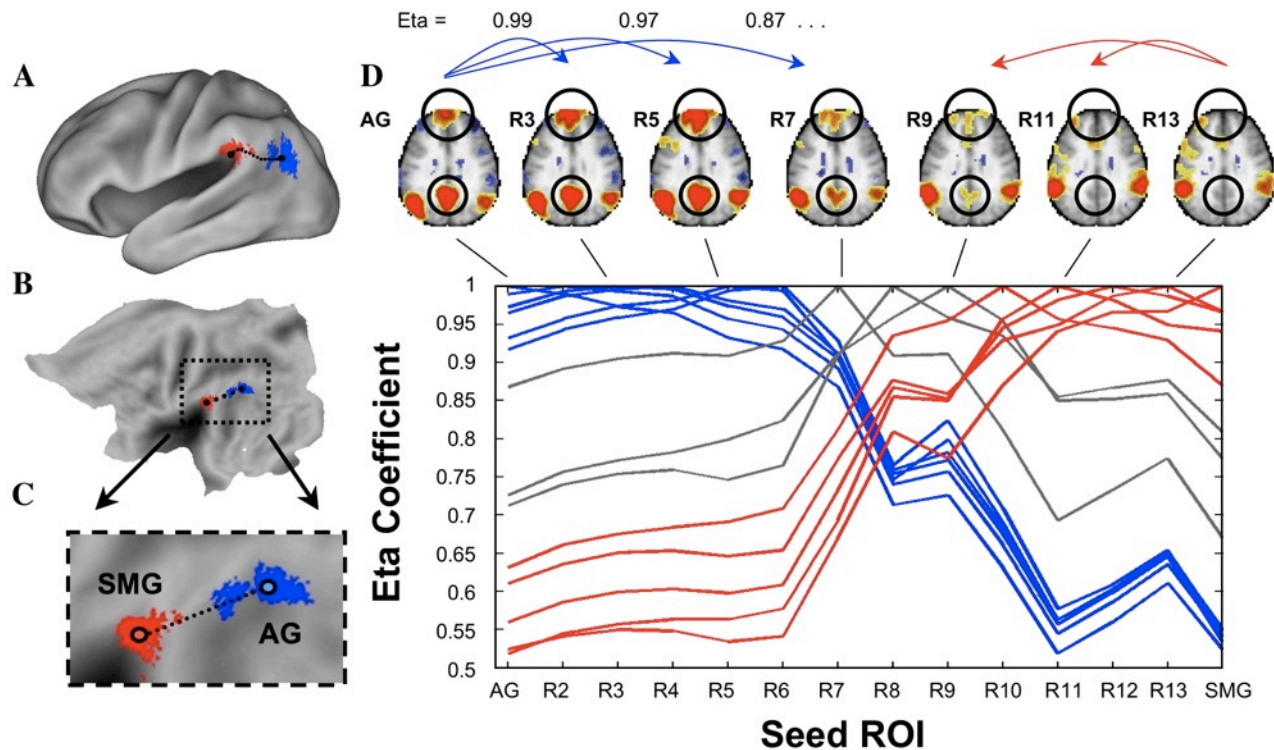


# 10 brain networks using ICA?



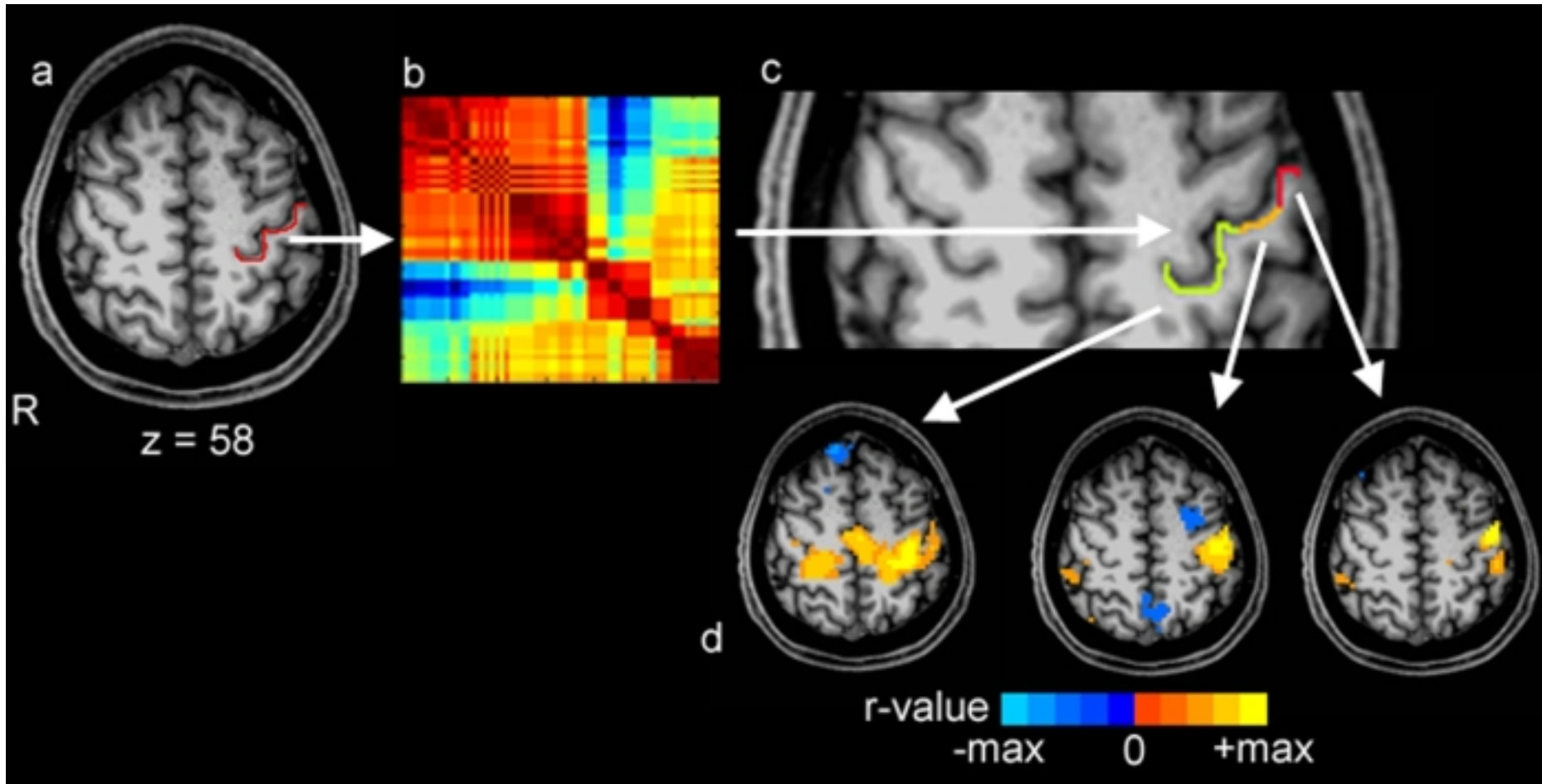
All these brain network counts are from the same respected lab!

# Clustering / Parcellation





# Parcellation of the Postcentral Gyrus

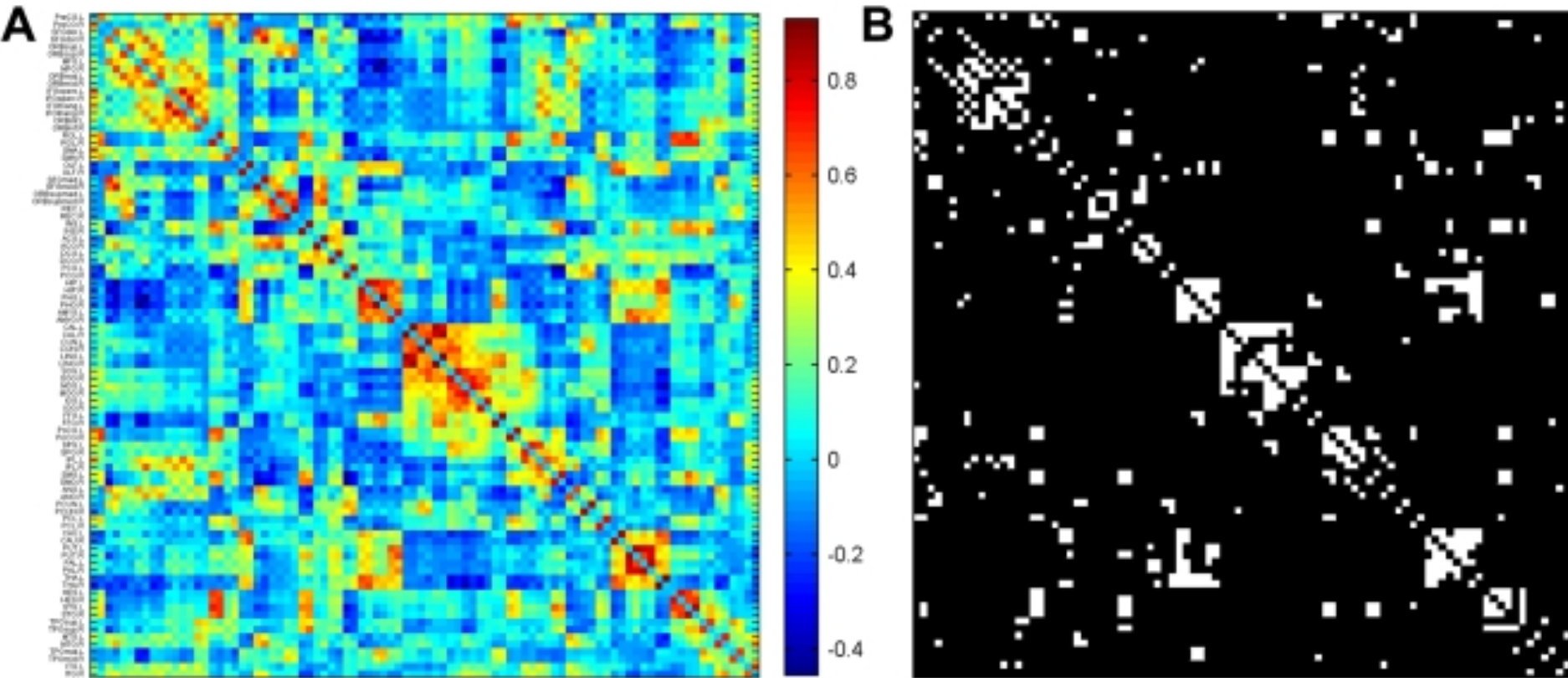




# Clustering + & -

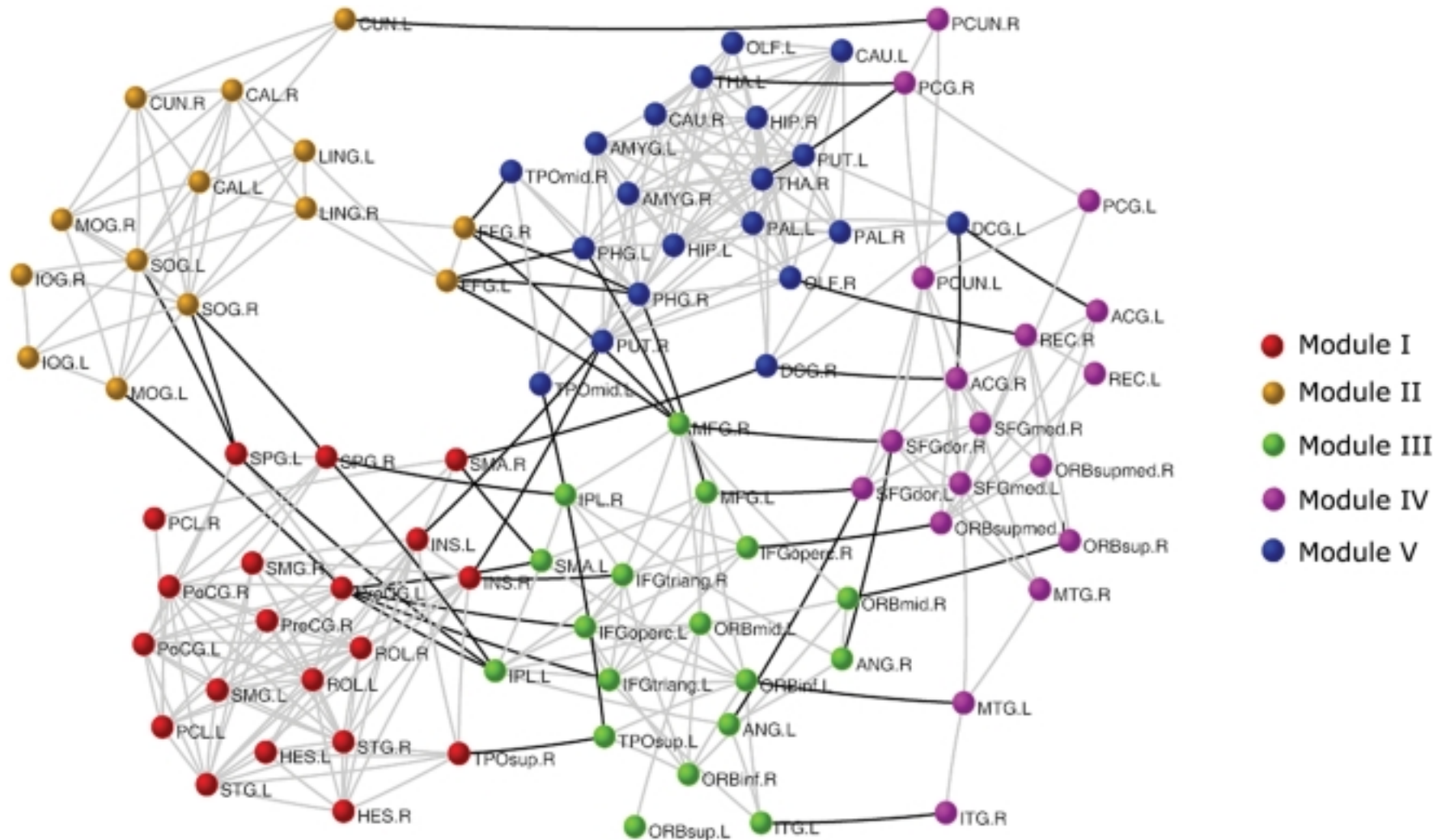
- + Potential for seeing clustering differences across populations
- + Useful for dividing brain by functional commonalities
- + Creates inputs to other analyses  
(cluster-based seeds)
- Some approaches are very sensitive  
to # of clusters requested
- You'll always get clusters whether or not they  
mean anything (no clear gold standard of accuracy)

# Graph Theory Approaches



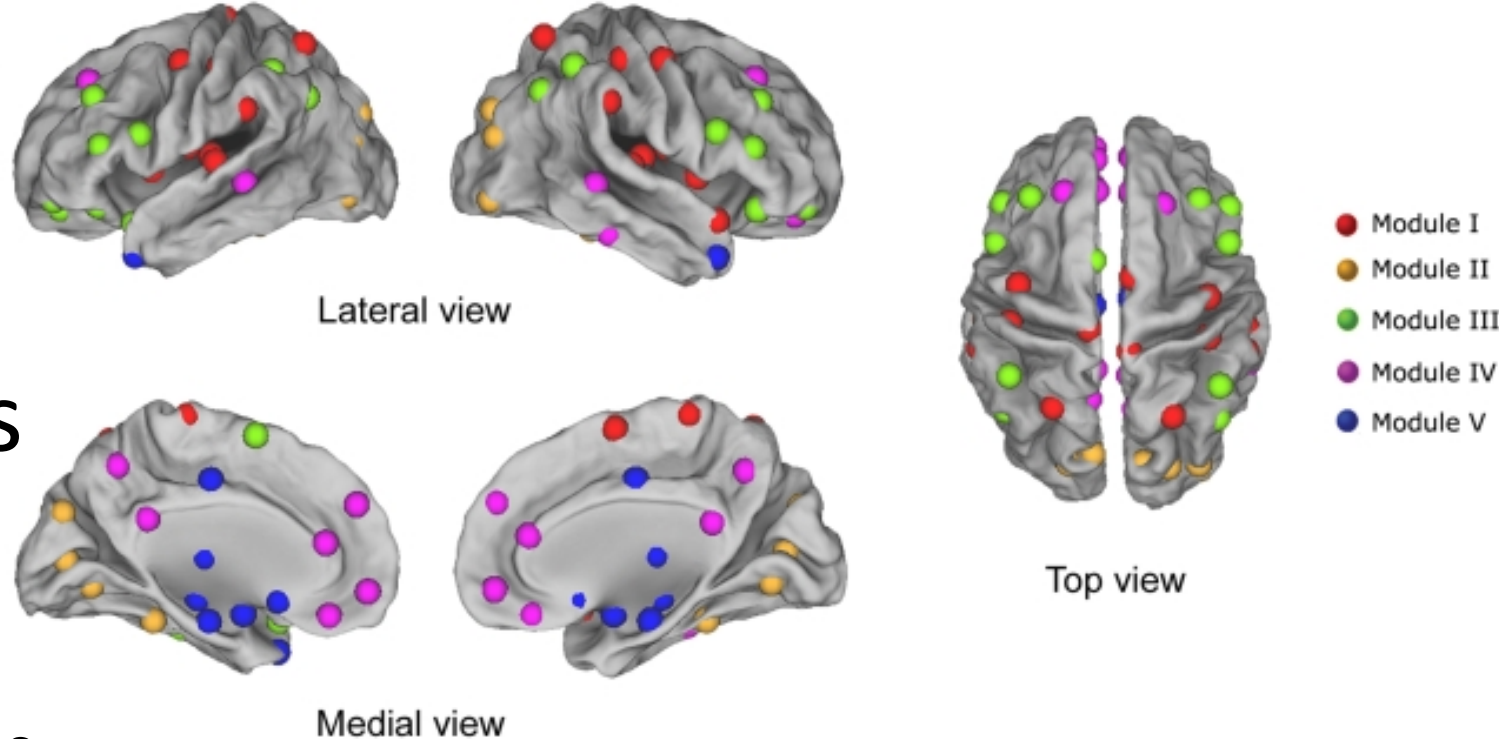
He et al PLOS ONE 2009

# Modular Brain Networks

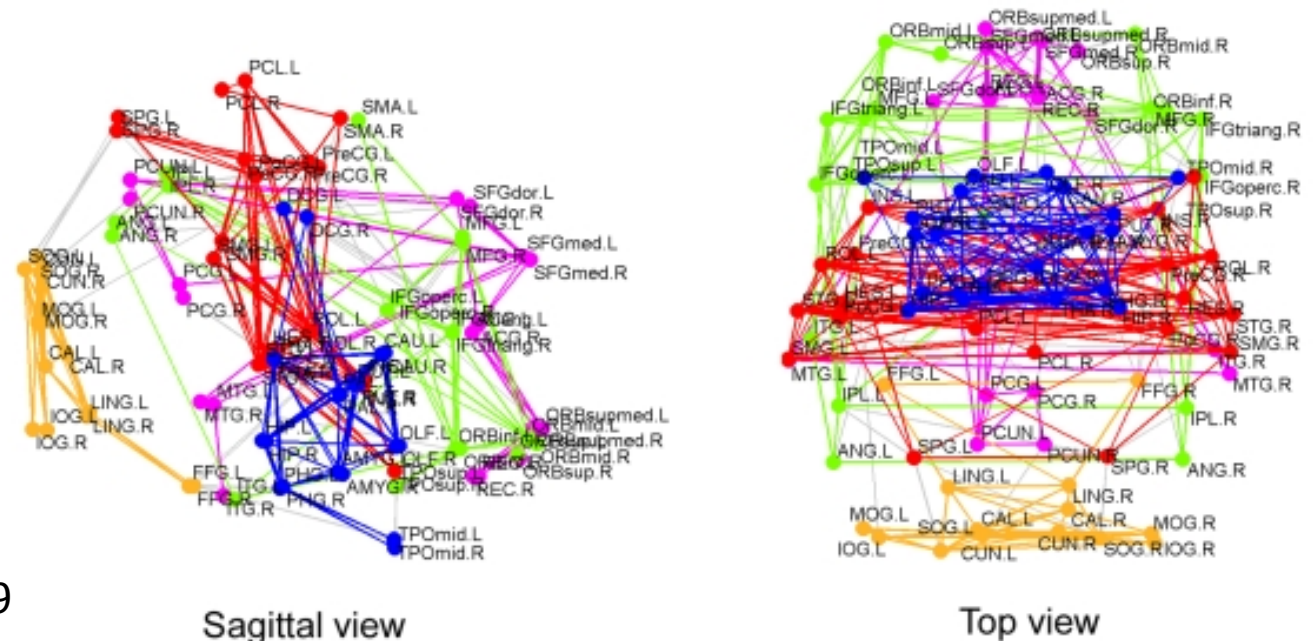


The closer the dots, the more similar their time series

# Modular Brain Networks

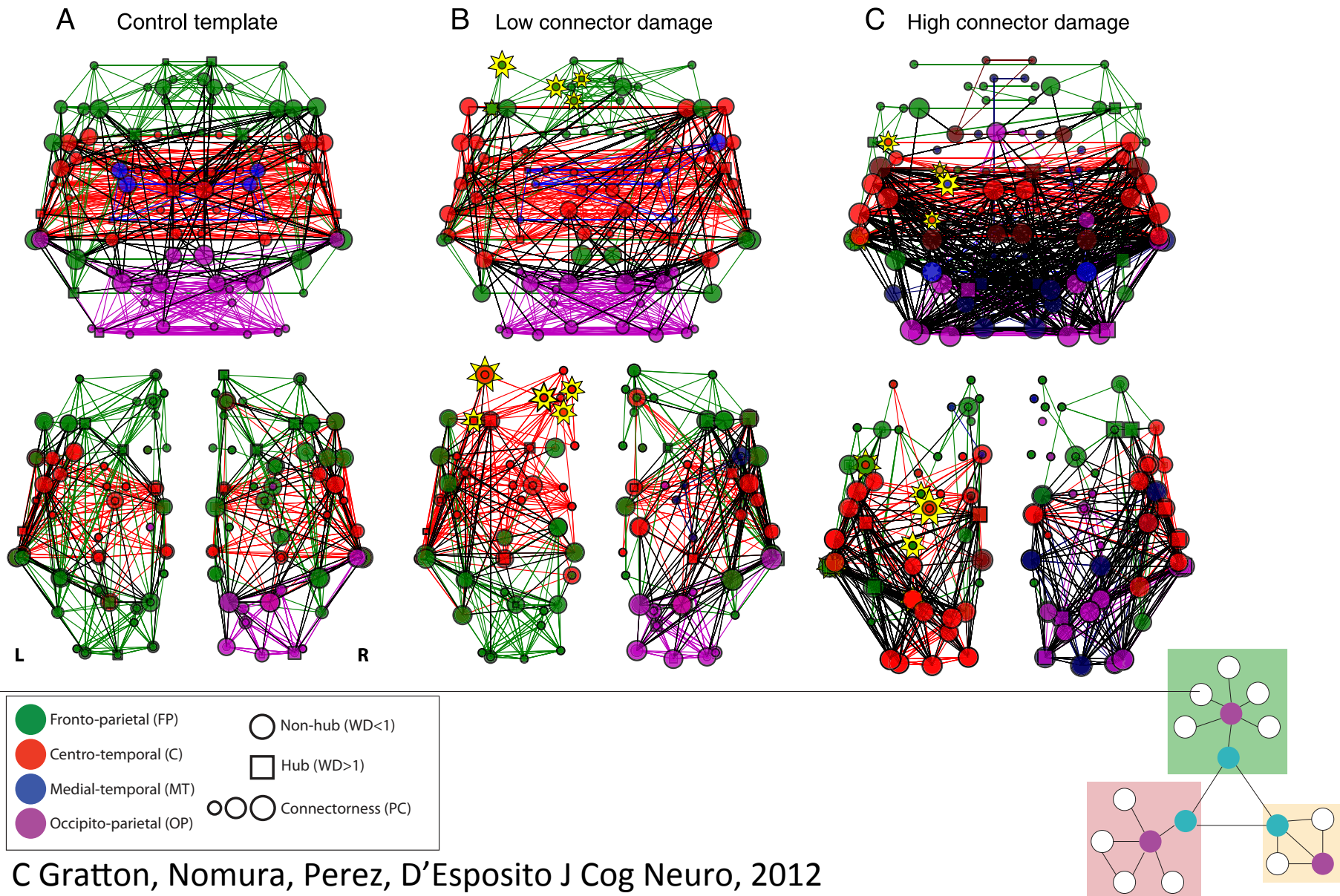


Same regions and connections as the last slide represented in brain-space

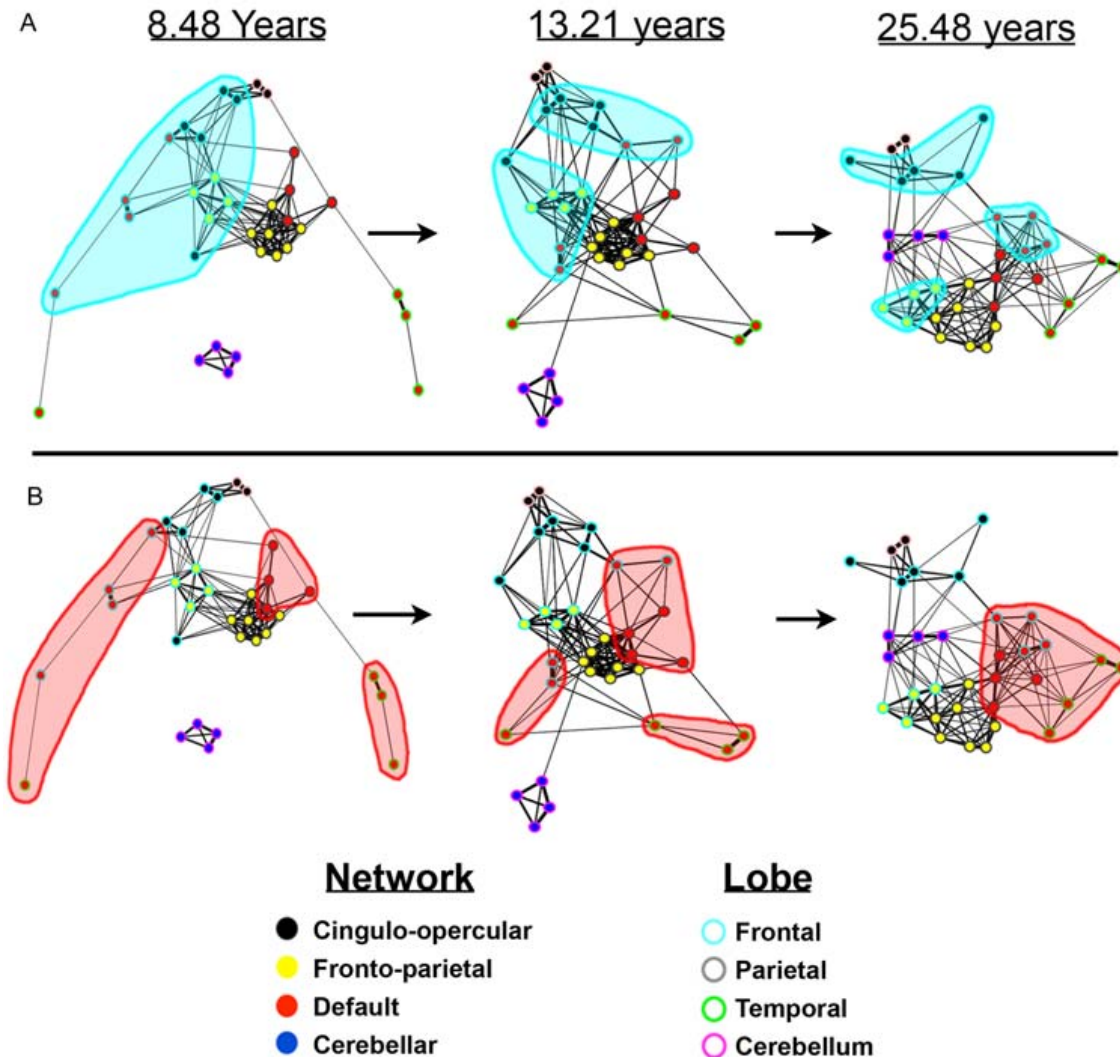




# Network disruption depends on stroke lesion location



# Functional Brain Networks Develop from a “Local to Distributed” Organization





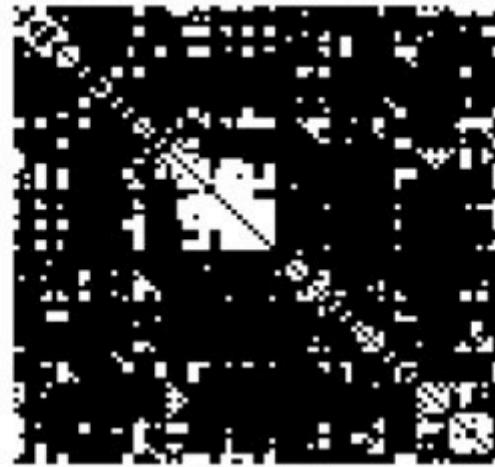
# Advantages of graph theory approaches

- Can make beautiful pictures (or ugly)
- Used for hypothesis generation and testing
  - Similarities between DTI & resting connectivity graphs (Honey, PNAS 2009)
- Can see how connections and segmentations change across populations
  - Graphs change in children with ADHD (Wang HBM 2008)
  - Graphs change with schizophrenia (Liu Brain 2008)
- The strength of seed-based correlations, with less worries about seed selection
- Potentially useful whole-brain-network metrics

# Disadvantages of large-scale interconnections



R=0.3



R=0.4



R=0.5



Basset & Bullmore The Neuroscientist 2006

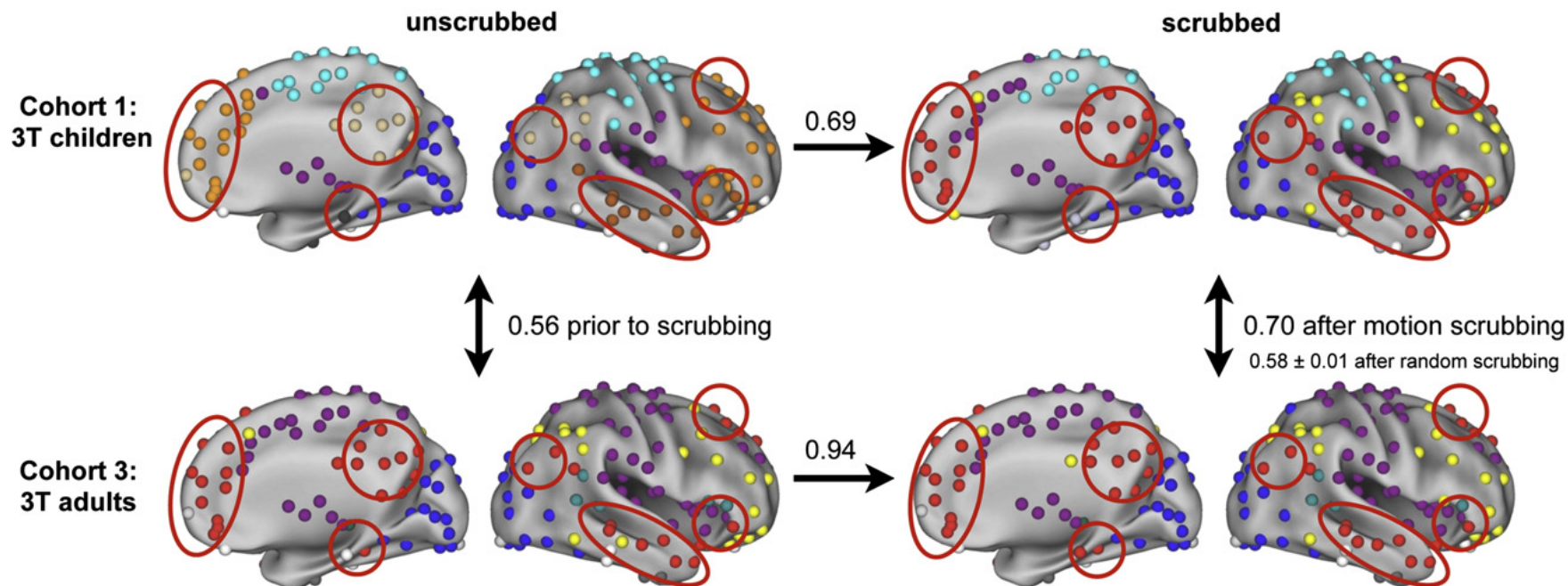
## Sensitive to how you build the network

What is the region size

What is the distance function?

What is significant?

# Preprocessing really matters



When they scrubbed data for areas of higher head motion (more common in children), the main network differences disappeared

Power, ... Petersen, Neuroimage 2012

“It really, really, really sucks. My favorite result of the last five years is an artifact,” Steve Petersen

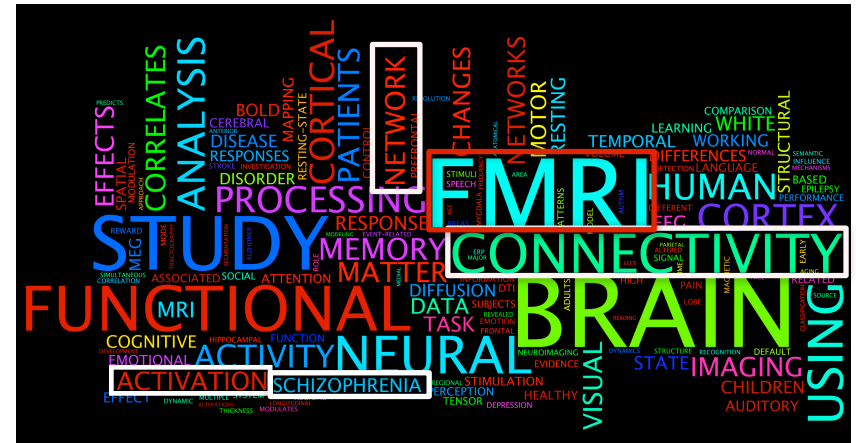
<http://sfari.org/news-and-opinion/news/2012/movement-during-brain-scans-may-lead-to-spurious-patterns>

# For better and worse, connectivity now dominates fMRI methods development

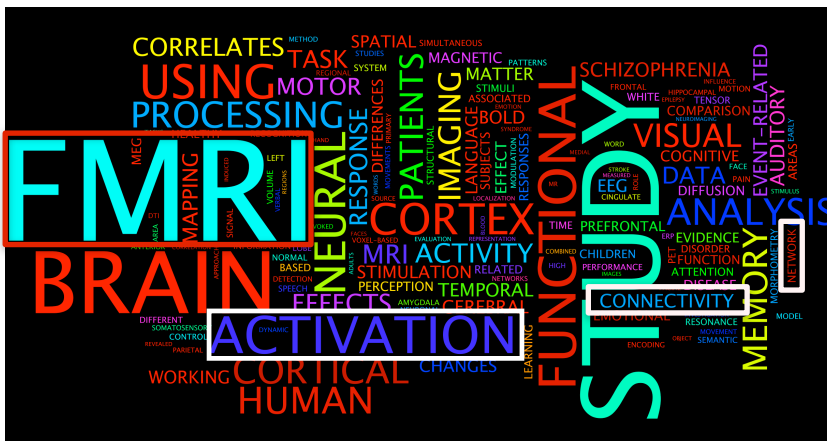
OHBM 2013



OHBM 2010-2012



OHBM 2003-2006



OHBM 2007-2009

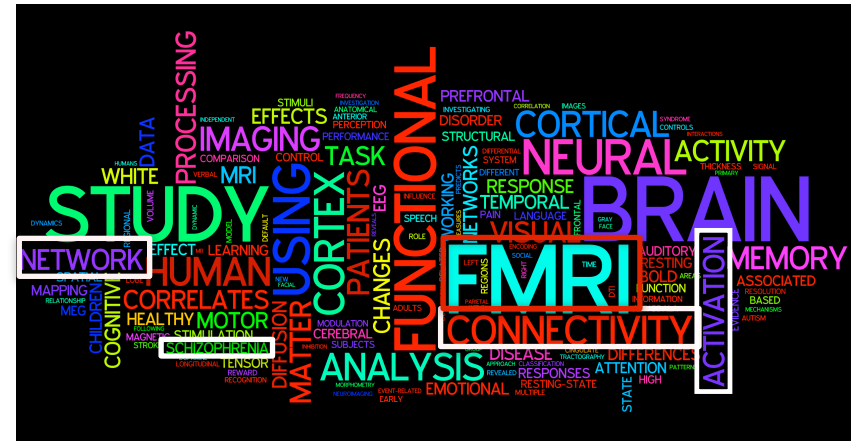


Image from Maurizio Corbetta

# Resting-State Summary

- It's really amazing this works!
- It's not always easy to tell when it doesn't work

## **Don't forget the scientific questions**

- How do we link functional connection maps to function?
- What differences are scientifically relevant?
- What disrupts fluctuations?
- How do we interpret differences across populations?

# Come back next week

Catie Chang & Steve Gotts

- Methods to remove noise
  - How imperfect noise removal causes problems
- EEG-fMRI, MEG, ECoG
- Coritcal layers with resting connectivity
- How connectivity changes over time
- More analysis methods
- Clinical applications
- The meaning of life



# Acknowledgements

**Slides and/or some talk ideas from**

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